Improving energy and economic performances of a typical sugarcane factory through energy indicator development, set-point optimization, and optimal sensor placement

By

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Abstract

The volatile sugar markets and the recent recognition of bagasse as a key feedstock to produce biofuels and bioproducts have prompted a desire in the sugarcane industry to correct energy inefficiencies thereby allowing for additional revenue from increased surplus bagasse availability. However, the desire for improved energy efficiency is often beset by the lack of adequate measurements, imprecise measurements, budget constraints, and random variations in external process disturbances and market prices. In this regard, this study seeks to evaluate optimal control solutions that can be used to enhance the plant-wide monitoring and control of existing process operations in a typical sugarcane mill that processes 250 tonnes of sugarcane per hour.

Objective 1 sought to identify the controlled variables (CVs) whose steady-state set-point deviations are associated with excess energy demands through energy indicator definition, sensitivity, and statistical analysis. An established sugarcane mill model was used to simulate the steady-state deviations of the CVs and to quantify their effect on energy usage based on defined energy indicators. Objective 2 entailed the use of Monte Carlo analysis to investigate the effect of process disturbances and market price variations on the steady-state factory control and net- revenue. Six disturbances were considered for simulation using the sugarcane mill model while the net revenue was defined in terms of raw materials cost and product revenue. From the observed steady-state deviations, set-point optimizing control (objective 3) was investigated for use in maximizing the net revenue by finding the optimal set-points for the CVs when disturbances and market prices vary. Fourteen CVs identified from objective 1 to have a large influence on energy consumption were used for set-point optimization.

From objective 1, massecuite recycling was identified to result in excess energy demands and with set-point optimization, recycling was reduced by 23%. Surplus bagasse was increased by 8.5% with an acceptable 0.43% reduction in sugar yield and a 2.4% increase in net revenue. Nine CVs were identified to have optimal steady-state set-points that are insensitive to disturbance variations, thus allowing for simplified implementation of set-point optimization by keeping these CVs at constant set-points while re-optimizing for the remaining 5 CVs. The availability of precise measurements is crucial for effective automated control. Hence, the self-optimizing control concept was used to find an optimal linear combination of 41 CVs and their optimal sensor placement for use as constant CVs while eliminating the need for frequent online re-optimization when disturbances occur (objective 4). Optimality is defined as maximizing the net revenue by minimizing the total cost of purchasing the measuring instruments and the average revenue loss due to implementing the constant set-point policy rather than continuous real-time optimization. The cost of purchasing the sensor is normalized based on its expected lifespan. The attained optimal sensor placement has an average revenue loss of US$61.93/hr while the base case sensor placement loss is US$157.72/hr. The reduction in average revenue loss is attributed to 19 CVs for which the optimal sensor placement allocated more precise sensors compared to the base case sensor placement. The cost of purchasing the more precise sensors for these 19 CVs is US$2.73/hr. Overall, this study was able to successfully formulate strategies for enhanced process monitoring and control in sugarcane mills while contributing to the available literature.

Opsomming

Die onbestendigde suikermarkte en die onlangse erkenning van bagasse as ’n sleutelfaktor vir die produksie van biobrandstowwe en bioprodukte het ’n begeerte in die suikerrietindustrie aangehits om energie-ondoeltreffendhede te korrigeer en daardeur addisionele inkomste uit verhoogde surplus bagasse se beskikbaarheid, toe te laat. Die begeerte vir verbeterde energiedoeltreffendheid word egter gereeld in beslag geneem deur die gebrek aan voldoende afmetings, onakkurate afmetings, begrotingsbeperkings, en lukrake variasies in eksterne prosessteuringe en markpryse. In hierdie verband poog hierdie studie om optimale beheeroplossings te evalueer wat gebruik kan word om die fabriekswye monitering en beheer van bestaande prosesbedrywighede in 'n tipiese suikerrietfabriek wat 250-ton suikerriet per uur verwerk, te verbeter.

Doelwit 1 het probeer om die beheerde veranderlikes (CV’s) te identifiseer wat se bestendige toestand setpuntafwykings geassosieer word met oormaat energievereistes deur energie-indikatordefinisie, sensitiwiteit, en statistiese analise. ’n Gevestigde suikerrietaanlegmodel is gebruik om die bestendige toestand afwykings van die CV’s te simuleer en hul effek op energieverbruik te kwantifiseer gebaseer op gedefinieerde energie-indikators. Doelwit 2 het die gebruik van Monte Carlo-analise behels om die effek van prosessteuringe en markprysvariasies op die bestendige toestand fabrieksbeheer en netto opbrengs, te ondersoek. Ses steuringe is oorweeg vir simulasie deur die suikerrietmeulmodel te gebruik in terme van rou materiale se koste en produkinkomste. Van die waargenome bestendige toestandafwykings, is setpuntoptimeringsbeheer (doelwit 3) ondersoek vir gebruik in maksimering van die netto opbrengs deur die optimale setpunte vir die CV’s te vind wanneer steuringe en markpryse varieer. Veertien CV’s wat in doelwit 1 geïdentifiseer is wat ’n groot invloed op energieverbruik het, is gebruik vir setpuntoptimering.

Uit doelwit 1, is massecuite-hersirkulasie geïdentifiseer om oormaat energievereistes tot gevolg te hê en met setpuntoptimering het hersirkulasie met 23% afgeneem. Surplus bagasse het met 8.5% verhoog met ’n aanvaarbare 0.43% afname in suikeropbrengs en ’n 2.4% verhoging in netto opbrengs. Nege CV’s is geïdentifiseer om optimale bestendige toestand setpunte te hê wat onsensitief is vir steuringvariasies, en het dus vereenvoudigde implementasie van setpuntoptimering toegelaat deur hierdie CV’s by konstante setpunte te hou terwyl die oorblywende vyf CV’s heroptimeer kon word. Die beskikbaarheid van presiese afmetings is

krities vir effektiewe geoutomatiseerde beheer. Daarom is die self-optimeringsbeheerkonsep gebruik om ’n optimale liniêre kombinasie van 41 CV’s en hul optimale sensorplasing vir gebruik as konstante CV’s, te vind, terwyl die behoefte aan gereelde aanlyn heroptimering wanneer steuringe voorkom (doelwit 4), geëlimineer word. Optimaliteit is gedefinieer om die netto opbrengs te maksimeer deur die koste van instrumentasie en die gemiddelde inkomsteverlies te minimeer as gevolg van die implementering van konstante setpuntbeleid in plaas van die aaneenlopende intydse optimering. Die behaalde optimale sensorplasing het ’n gemiddelde inkomsteverlies van US$61.93/hr terwyl die basis-geval sensorplasing se verlies US$157.72/hr is. Die vermindering in gemiddelde inkomsteverlies word toegeskryf aan 19 CV’s waarvoor die optimale sensorplasing meer presiese sensors geallokeer het in vergelyking met basis-geval sensorplasing. Die koste van die presisie opgradering vir hierdie 19 CV’s is US$2.73/hr. Oor die algeheel het hierdie studie suksesvolle strategieë vir versterkte prosesmonitering en -beheer in suikerrietmeule geformuleer, terwyl dit tot die beskikbare literatuur bygedra het.

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Lastly, I dedicate this work to the treasured memory of my beloved young brother, Sijabuliso.

"*Now this not the end. It is not even the beginning of the end. But it is, perhaps the end of the beginning*"

Sir Winston Churchill

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Terms and Definition

Bagasse	The fibrous residue after sucrose extraction from sugarcane
Calandria	Tubular or plate heating element in an evaporator vessel
Dissolved solids	Solute material (e.g. sucrose, monosaccharides, ash, and organic impurities) in solution
Dry substance	A measure of total solids obtained from evaporating a solution under vacuum to dryness.
Energy indicators	Energy performance measures that are used to monitor and benchmark the energy efficiency of the whole system or its various units.
Imbibition water	Water added facilitating sucrose extraction from sugarcane.
Magma	A mixture of sugar crystals and syrup from the mingler. The mixture is used as seeding material for sugar crystallization.
Massecuite	The mixture of sugar crystals and mother liquor.
Mingler	Mixing tank for sugar crystals and syrup.
Molasses	The liquid separated from sugar crystals by centrifuging.
Mother liquor	The liquid phase in the massecuite during crystallization.
Revenue loss	Difference between the net revenue when online optimization is done and the revenue when no optimization is done with the occurrence of disturbances (self-optimizing control)
Self-optimizing control	A control strategy that seeks to eliminate the need for frequent re-optimization when disturbances occur by keeping a combination of measured controlled variables (CVs) at constant set-points while operating near the optimal steady-state operating conditions in presence of disturbances and measurement errors.
Sensor precision	Degree of agreement among several consecutive measurements of a variable with a fixed value.
Set-point optimization	Control strategy that uses a process model and optimizer offline or online to maximize factory revenue by re-computing new optimal set-points according to values of the disturbances.
Syrup	Concentrated juice from the evaporator unit.

Abbreviations

CDF	Cumulative distribution function
CV	Controlled variables
DS	Dissolved solids
GAs	Genetic Algorithms
HTC	Heat transfer coefficient
HP	High-pressure
K-S test	Kolmogorov–Smirnov test
LP	Low-pressure
MPC	Model-predictive control
MSV	Minimum singular value
PDF	Probability distribution function
RECA, RECB, and RECC	Massecuite recycling in A, B, and C vacuum pan
RTO	Real-time optimization
RV	Recoverable value
SB	Syrup dissolved solids concentration
SOM	Supplementary online material
SOP	Standard operating procedure
VPA, VPB, and VPC	A, B, and C massecuite temperature in the boiling pans

Other abbreviations used as equipment and stream tags are provided in Table 2-1 to 2-6.

Chapter 1

1. Introduction

Sugarcane is an important agricultural crop that has a major contribution to the gross national product of over 88 nations, including developing countries such as China, India, and South Africa [1,2]. The sugarcane stalk is composed of 65-75% water, 10-18 % fiber, 10-15% soluble sugars (sucrose), and 2-3% non-sugars [3]. The sucrose component is extracted for sugar production, while the fiber (bagasse) is incinerated in the boiler unit to produce superheated steam of around 390˚C and 31 bars [4]. The superheated steam is used to sustain the energy demands of the sugarcane mill operations by providing energy to drive the factory machinery and producing electricity and process heat (exhaust steam) in the turbogenerators. For a sugarcane factory designed for energy efficiency, all the process energy requirements may be met by partial combustion of bagasse, while simultaneously generating surplus bagasse and eliminating the need for using expensive supplementary fuel [1,3]. In the past, there was no justifiable use for bagasse hence sugarcane factories were operated and designed to be energy-inefficient to avoid excess bagasse disposal costs [1,3]. Hence sugarcane processing focused on extracting sucrose efficiently to maximize revenue from sugar production and minimize production costs associated with surplus bagasse disposal [1,3,5,6].

With the unpredictable world sugar markets, interest is growing among the global sugar manufacturers to diversify their revenue stream from sugar production through the use of the main by-products, molasses, and bagasse, in the production of high-value bioproducts [7–9]. This interest coincides with the increasing global awareness of reducing fossil resources, which have made bagasse to be widely acknowledged as one of the best feedstocks for the production of renewable electricity, biochemicals, and biofuels [1,3]. Revenue diversification seeks to maintain a stable revenue base for the sugarcane industry by creating additional and multiple revenue streams that contribute substantially to the overall factory profitability. As such, the sugarcane industry, with its abundant bagasse supply, is envisaged to financially benefit by participating in the large-scale commercialization of biofuels and bioproducts [1,3,5]. To enable the generation of surplus bagasse for valorization, it is considered essential to evaluate the closed energy balance approach used by the sugarcane mills to be energy self-sufficient without generating excess bagasse. The inefficiencies in the sugar production operations result in high demand for bagasse energy while the inadequate control of the boiler results in increased bagasse energy wastage [6,10]. For these reasons, the selected strategy must entail the use of precise sensors and suitable control policies to ensure the accurate estimation and correction of excess energy demands or wastage in sugarcane mills [11–14].

The inherent randomness of the process disturbances and market prices, the intricate interaction of the process unit operations, cost constraints, inadequate measurements, and automated control is reported barriers to energy efficiency improvement in sugar mills [14–17]. The process disturbances in the context of the present study refer to external disturbances that have nothing to do with the controllers' efforts and are thus unavoidable to the cane sugar manufacturers. For example, the variation in the sugarcane composition because of cultivars and climate effect on the growth of sugarcane as well as sugarcane supply inconsistencies due to harvesting delays in the rainy season [18]. Such variations compromise the control systems' ability to maintain the desired operating conditions thereby resulting in frequent plant stoppages and process transients which are further expedited by the intricate interaction of the process unit operations [6,19]. The changes in the market prices influence the factory revenue, while the variations in the external process disturbances lead to deviations in the steady-state set-points of the controlled variables. For successful revenue diversification, the different revenue streams need to be strategically managed [1]. However, considering the high frequency of variation of the market prices, a systematic strategy is required that will enable the cane sugar manufacturers to balance energy efficiency (bagasse revenue) and sugar production improvement (sugar revenue).

Despite the acknowledgment of the high variation frequency of the market prices and external process disturbances, most studies model these variables using their fixed or seasonal averaged values rather than accounting for their randomness [20]. Hence, the resulting optimal control and design solutions are only optimal for the considered process disturbance values and market prices and leave the sugarcane mill operations vulnerable to the inevitable variations of these variables [20]. Furthermore, the sugarcane mill comprises many process units that are intricately connected or dependent on one another through energy or feed flow supply. As such, the steady-state deviation of a particular controlled variable from its desired value can adversely influence the production and energy performance of the downstream process units [6,21]. However, there is limited research that quantitatively evaluates how the steady-state set-point deviations in one unit influence the energy efficiency of the other process units it interacts with through energy or feed flow supply. Such evaluations can enable the mathematical and logical determination of appropriate corrective actions for the individual process units, based on their energy or feed flow supply interaction with other factory process units. In this way, the operation of each process unit is done in consideration of the other process units it interacts with so that the main goal is to reduce the plant-wide energy and economic inefficiencies in a sugarcane factory.

With increasing industrial competition, energy prices, and awareness of global warming-related to climate change, manufacturing industries face intense pressure to sustain their economic viability through cautious usage of energy [22–24]. For these reasons, there has been a growing interest among policymakers and manufacturing industries in the role that industrial energy monitoring and benchmarking can play in climate change and reduction of industrial manufacturing costs [22–24]. Energy indicators are tools used to monitor and benchmark the energy performance of the overall factory operations or its various process units [22,23,25]. Energy indicators are often defined as the ratio of the output of useful energy (or product) to the total energy input [26]. Although these energy indicators are useful for energy benchmarking and reporting, recent studies have argued that they provide inadequate detail for systematic allocation and correction of the variables responsible for excess energy demands [25,27–29]. Hence recent studies are focused on understanding the correlation between process activities and energy indicators by developing causal models and encouraging industries to define energy indicators based on variables with the largest impact on energy usage [6,11,30]. While supervised learning models are often used, other non-supervised techniques like Principal Component Analysis and Multiway Principal Component Analysis have also gained traction for use in energy monitoring continuous and batch processes, respectively [27–29].

However, most of the energy indicators used in the sugarcane mills are defined as ratios of the useful output to the input energy, for example, the steam used per tonne sugarcane processed [11,26]. In case of a deviation from the specified energy indicator benchmark, these energy indicators provide limited information on the process variables contributing to the observed deviations such that appropriate corrective actions are implementable. Such information can also allow for a better understanding of the energy trends and identification of energy wastage areas with a potential for improvement through the implementation of optimal control policies. Energy monitoring and control is a continuous energy efficiency improvement practice based on the principle “you cannot manage what you cannot measure” [31]. As such, in addition to the requirements of suitable energy indicators, adequate and precise measurements are required to ensure precise energy usage estimation and correction.

However, sugarcane mills have been reported to lack adequate instrumentation and precise measurements for effective energy monitoring and control [14,16]. The use of precise measurements combined with good control systems enables the shifting of the control set-points closer to the safety or operating constraints, which harbor the greatest energy-savings and profit gains [32]. Furthermore, precise measurements allow for the implementation of energy improvement strategies like pinch analysis [33] or vapor usage reconfiguration [34], based on precise energy consumption estimations and evaluations. The cost of purchasing instrumentation tends to rise with an increase in the number and precision of the sensors. This awareness, reinforced by budget constraints, leads to resistance in investing in newer technology or sensors for improved energy monitoring and factory control [12,35]. Hence, there is scope to design a plant-wide sensor network for the sugarcane mills that considers both the cost of instrumentation and the economic benefits of more precise sensors. This will address the instrumentation problems while allowing for effective energy monitoring and plant-wide control. These improvements can result in improved factory profitability and increased capability for existing sugarcane mills to be annexed to a relatively larger bio-refinery due to the increase in surplus bagasse feedstock.

1.2. Study aim, objective, and task definition

The overall aim of this study is to develop an improved energy monitoring and management system for existing equipment in a typical sugarcane mill through enhanced process monitoring and plant-wide control. The primary objectives set out to achieve the study aim are to:

1. Determine the CVs whose steady-state deviation leads to excess energy consumption, through energy indicator definition, sensitivity, and statistical analysis
2. Evaluate the stochastic risks associated with the random variations in the process disturbances and market prices
3. Investigate the potential benefits of implementing set-point optimizing control when process disturbances and market price variation occur.
4. Find an economically optimal sensor placement for a typical sugarcane mill based on the self-optimizing control concept and genetic algorithms.

1.2.1. Predictive energy indicator development

Energy indicators are defined for monitoring the energy consumption of process units and overall factory, to provide a basis for estimating and reporting the energy performance relative to the target. The steady-state value deviations of nine selected controlled variables (CVs) are simulated using the steady-state model of a typical sugar mill that processes 250 tonnes per hour of sugarcane. This is done to investigate the effect of the steady-state deviations of the CVs on the defined energy indicators and identify the CVs whose steady-state value variations have the largest impact on energy usage. A full factorial design of the steady-state value variations is used for the model-based sensitivity studies, hence enabling the understanding and quantitative analysis of the process unit's interaction from an energy perspective. The sensitivity analysis results are used to develop predictive energy indicators based on the CVs whose steady-state deviations are shown to result in excess energy demands. Hence providing energy indicators that can be used for process monitoring and targeting based on the CVs with the largest energy usage influence, while stimulating team effort and dialogue amongst plant personnel on possible energy improvement measures.

1.2.2. Stochastic modeling of disturbances and set-point optimization

To conduct comprehensive energy and economic evaluation of the stochastic risks associated with variations in the process disturbances and market prices, the Monte Carlo approach is used in the present study. The Monte Carlo approach randomly chooses the input values of the process disturbances and market prices from their probability distributions, which follow their real-life factory variations [20]. The values of the process disturbances and market prices are randomly sampled from their estimated distributions and the sampled values are in turn used as inputs in the steady-state sugarcane mill model and the financial model. Since the study focuses on plant-wide operation, an accurate model of the steady-state mass and energy balances of the entire sugarcane processing system is required. Hence careful assessment of the available sugarcane mill models was done for the selection of the steady-state model used in the present study. Sugarcane flow, fiber, sucrose, and dissolved solids content, as well as air temperature and humidity, are the process disturbances considered in the present study. To translate the control objectives to economic objectives, the financial model is defined as the net- revenue (J), which considers the monetary expenditure for the raw materials (sugarcane and lime) and the product's revenue (sugar, molasses, and surplus bagasse).

For optimal steady-state control and profitability improvement, the set-points for the CVs must be selected such that they lead to the optimal adjustment of the manipulated variables, based on the available control structures. Such a steady-state optimizing control structure is especially pertinent when operating under the inevitable random variations of the process disturbances and market prices. Hence the study further seeks to use the Monte Carlo approach to investigate and illustrate the potential benefits of using set-point optimization for optimal control when operating under the random variations of the external process disturbances and market prices. The goal of set-point optimization is to maximize the factory net-revenue, J, by recomputing the optimal set-points for the CVs when process disturbances and market price variations occur. Fourteen CVs whose steady-state value deviations are identified from the fulfillment of objective 1 to have a large influence on the sugarcane mill operations are used as decision variables in the set-point optimizer that uses the surrogate global-optimization algorithm. Therefore, the set-point optimizer provides the optimal set-points which the controller attempts to implement to ensure optimal (maximum) net revenue, Jopt. The energy indicators defined from objective 1 are used to illustrate and quantify the energy benefits of set-point optimization.

1.2.3. Optimal sensor placement based on self-optimizing control

For the actual implementation of online set-point optimization in a factory, online measurements of the disturbances must be available, and all the resulting optimization problems must be solved online using an accurate process model. For a factory with a high frequency of variations, such computations can be intractable while such an implementation can be challenging for a factory with no online measurements of the disturbances [36]. Sugarcane factories are reported to experience a high frequency of sugarcane flow and composition variations towards the end of the harvesting season and during the rainy season. Moreover, the available technologies for disturbance measurements related to the sugarcane composition are based on laboratory analysis. To avoid implementing online set-point optimization, Skogestad [36] introduced the self-optimizing control concept as a simplified control alternative. In self-optimizing control, instead of attempting to attain the maximum net-operating revenue (Jopt), a small trade-off is made between factory profitability and the simplicity of not having to re-optimize every time there are variations in the unavoidable process disturbances [36]. For the actual implementation of self-optimizing control to be possible, a linear combination of measurements must be found for use as CVs whose set-points are held constant without online set-point optimization when disturbances occur.

However, by not optimizing factory operations in the presence of disturbances, self-optimizing control results in a loss in revenue, L, as compared to the truly optimal operation when online set-point optimization is done [36]. The loss in revenue is because of the combined effect of the disturbances and measurement errors on the controllers' attempt to implement the constant set-point policy (self-optimizing control). Therefore, to minimize the loss in revenue a search through all available combinations of measurements is done to find an optimal linear combination of CVs that will result in minimal revenue loss when used for facilitating self-optimizing control in a factory. Owing to its simplified approach to process control, self-optimizing control can be extended to other disciplines in the economy or social sciences sectors [36-38]. For example, in central bank management where the goal is to maximize welfare while maintaining the inflation rate at a constant value by manipulating the interest rates. Previous studies have used the self-optimizing control concept to find a linear combination of measurements for use as constant CVs in chemical reactors [37], distillation plants [36], evaporator systems [38], and many more applications. However, the adopted approach in these studies entails a search through fixed measurements with already established sensor precisions or measurement errors. Hence no study has used the concept to systematical determine the right sensor precisions for the linear combination of CVs such that better self-optimizing properties are achieved. Earlier studies for finding self-optimizing CVs use the brute-force approach [37]. However, for large processes, such exhaustive searches can be computationally intractable, hence methods like a branch and bound and genetic algorithms are becoming more preferred [38].

Therefore, the final study objective seeks to extend the self-optimizing control concept for optimal sensor placement using genetic algorithms. This entails the simultaneous determination of the optimal linear CV combinations and their corresponding optimal sensor precisions required for facilitating self-optimizing control in sugarcane mills. Optimality for sensor network selection is defined for maximizing the factory net-revenue by minimizing the total cost of purchasing sensors and the loss in revenue, L, because of the effect of disturbances and measurement errors on the controller's attempt to facilitate self-optimizing control. The cost of purchasing the sensor is normalized based on its expected lifespan. Hence the approach used in this study simultaneously addresses the sugarcane industry’s need for instrumentation, precise sensors, and improved process control when disturbances occur in a manner that economically benefits the industry and justifies investments in additional sensors. Through the extension of the self-optimizing control for optimal sensor placement, the present study further contributes to the available literature. In addition to an improved and simplified implementation of plant-wide control, the proposed strategy can enable precise energy usage estimation in sugarcane mills, thereby allowing for the identification of areas of energy wastage and the formulation of corrective actions.

1.3. Dissertation outline

Following the study background, Chapter 2 presents a review of the relevant literature on the sugar production process, energy indicator definition, set-point optimization, and self-optimizing control. Following the established research gaps and industry needs from Chapter 2, the research rationale and methods used in this dissertation are detailed in Chapter 3. Chapters 4 to 7 are individual studies, which have been prepared in an article format for journal publication. In Figure 1-1, the relationship between the objectives and the respective work chapters is presented together with the summary of anticipated novel contributions of each. In Chapters 4 and 5, the impact of the steady-state deviation of the CVs on the energy consumption of the factory is evaluated for the sugar production operations and boiler, respectively. Statistical analysis is used to identify the CVs whose steady-state deviation has the largest influence on energy efficiency and to develop energy indicator correlations based on the identified influential CVs.

Chapter 6 entails the stochastic modeling (using Monte Carlo) of the process disturbances and market price variations into the selected sugarcane mill model and financial model, respectively to evaluate their impact on factory control and profitability. Based on the observed impact, set-point optimization is then assessed in Chapter 6 for use in improving the profitability, process control, and energy efficiency of the sugarcane mill operations. This entails finding optimal CV set-points that the controller attempts to implement when process disturbances and market price variations occur. To address the inadequate instrumentation, lack of precise sensors, and budget constraints in sugarcane mills, Chapter 7 entails the selection of an economically optimal sensor placement using genetic algorithms and the self-optimizing control concept. The study is concluded in Chapter 8 with final remarks on the contribution to knowledge attained from the study and recommendations for industrial implementation and future research.

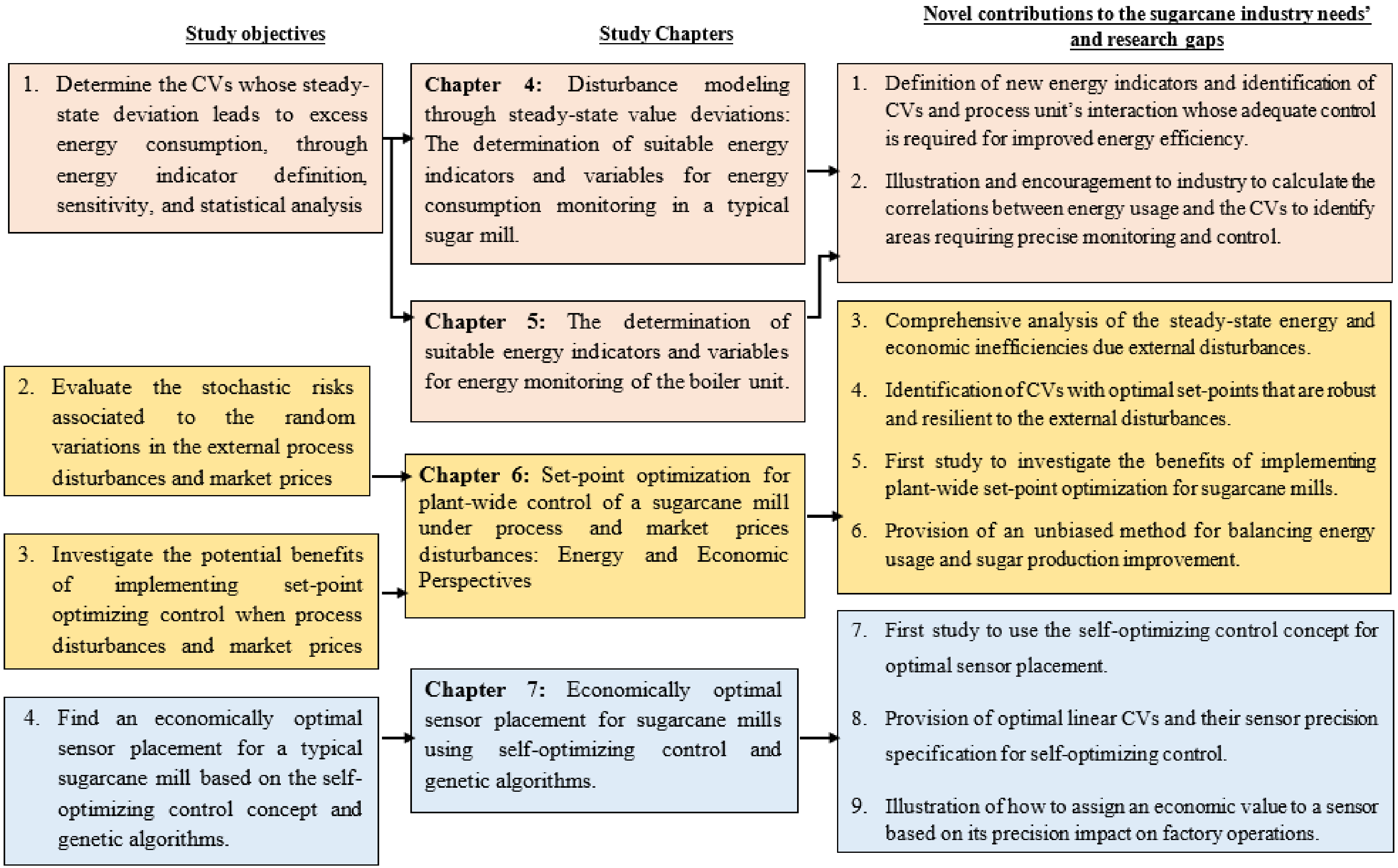

Figure 1-1: Outline and novel contributions of chapters 4 to 7

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Chapter 2

2. Literature Review

The outline for Chapter 2 is shown in Figure 2-1. the first part entails a critical review of relevant literature on the sugarcane mill processes and energy consumption perspective to identify the causes of energy and economic inefficiencies in a typical sugarcane factory. Based on the identified causes of energy and economic inefficiencies, Section 2.3 to 2.4 seeks to review the available energy management studies to identify the current research gaps relative to the industry needs to address inefficiencies. The identified research gaps and industry needs are in turn used in Chapter 3 to formulate the present study methods for addressing the industry needs while strengthening the currently available literature.

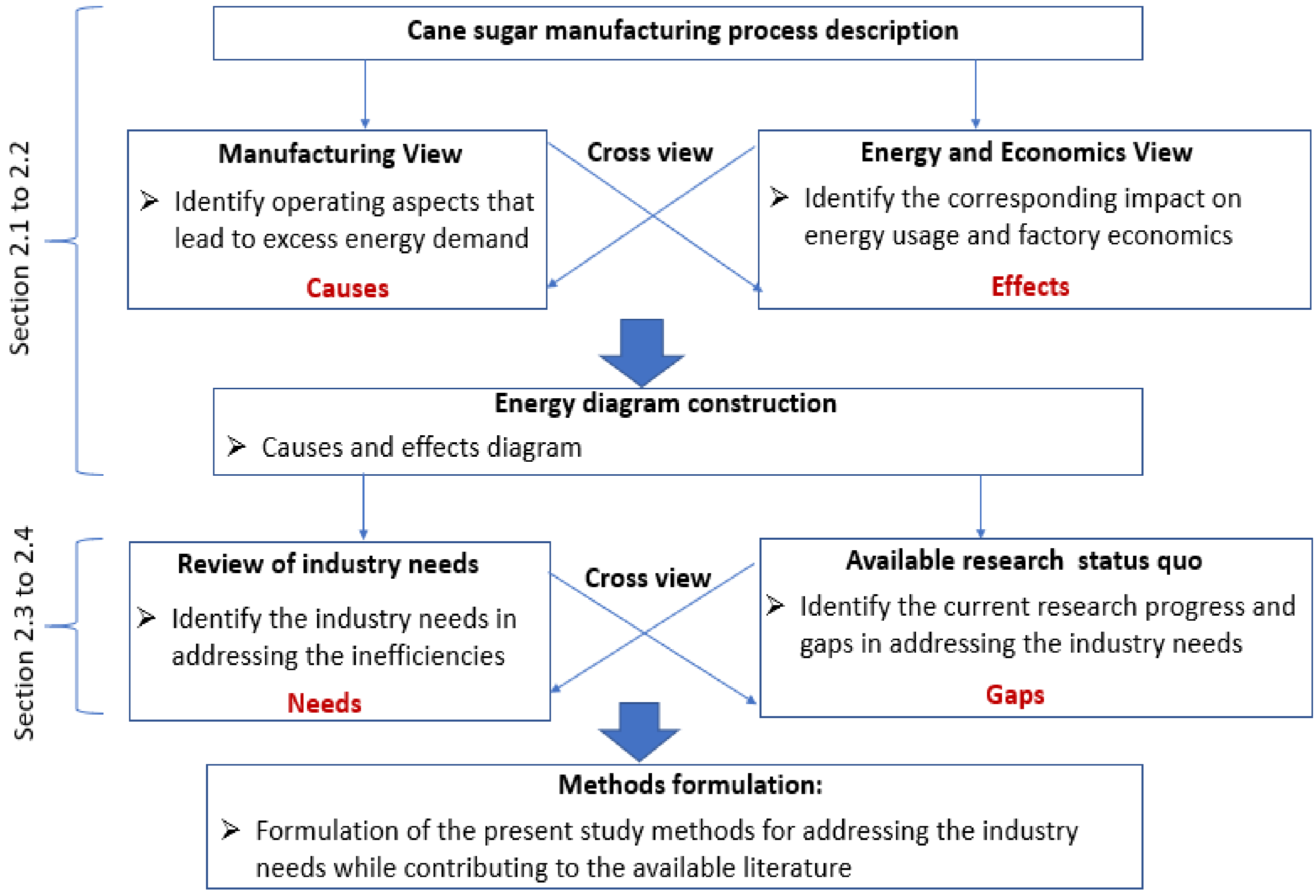

Figure 2-1: Outline for Chapter 2

2.1. Sugar production from sugarcane

Figure 2-2 is a simplified block diagram of a typical sugarcane factory. The raw sugar production process is divided into 5 main production units for juice extraction, clarification, evaporation, crystallization, and drying of the resultant commercial sugar. There are 4 main utilities namely the boiler, mill turbines, turbogenerator, and the cooling tower, which are used to provide superheated steam, mechanical driving power, electricity, and cooling water. A portion of the superheated steam generated from the boiler is used in the steam turbines to provide mechanical power for the extraction unit machinery, while the majority of the steam is used in the turbogenerators to produce electricity for the factory operations. The exhausted low-pressure steam from the backend of the mill turbines and the turbogenerator is used as process steam. The terms high-pressure (HP) and low-pressure (LP) steam are used throughout this dissertation to distinguish between the superheated steam from the boiler and the exhausted steam from the back-end of the turbines and turbogenerator, which is of lower pressure.

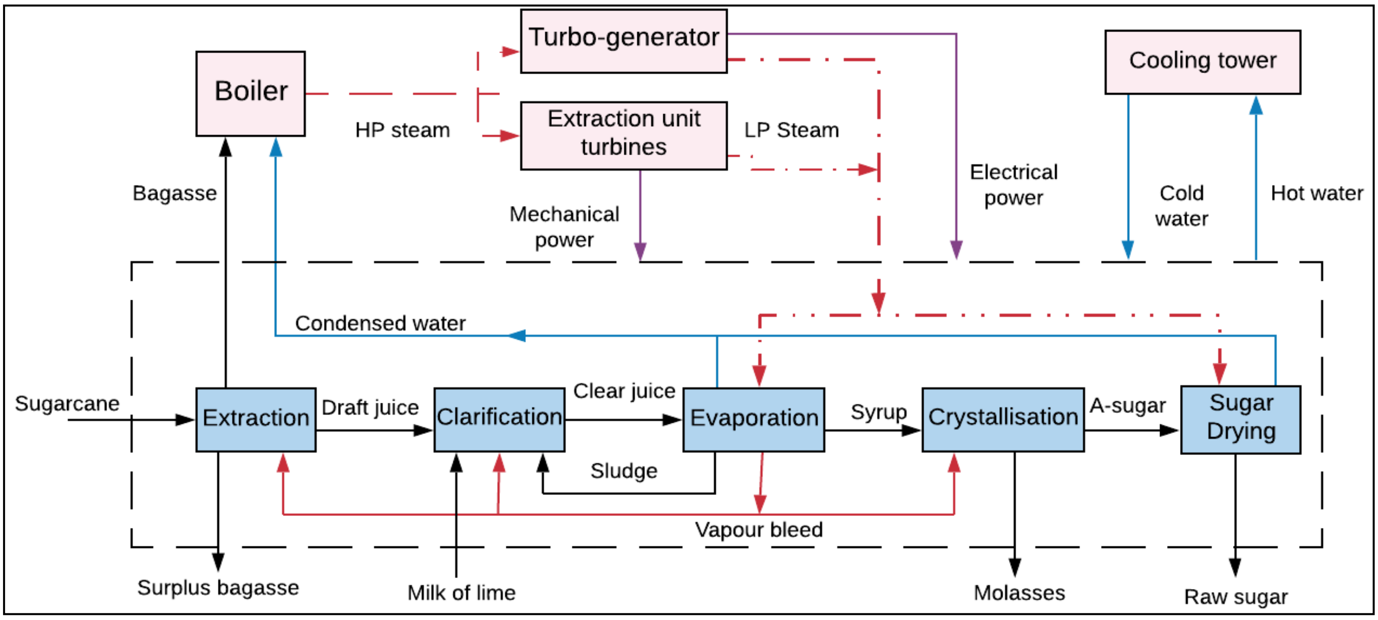

Figure 2-2: Simplified process flow diagram of a sugarcane mill

The first step in the production of raw sugar is the cutting and shredding of the sugarcane to prepare it for sucrose extraction in the diffuser or milling tandems [1]. The juice from the diffuser commonly termed draft juice is heated, limed, flashed, and clarified to remove the impurities that contribute to the opaque color of the juice [2]. The clarified juice (generally known as clear juice) is fed into the evaporator unit where it is concentrated to produce syrup. The syrup is fed to the crystallization unit where it is boiled under vacuum until crystals start to form. At this point, seeding material (syrup and fine crystals) is added to aid the sugar crystallization process [3]. The commercial-grade sugar from the crystallization unit is then dried and cooled in a rotary sugar drier.

The fiber residue, bagasse, remaining after sucrose extraction is first compressed in the dewatering mill before being used as fuel in the boiler to produce HP steam [4]. The HP steam is used in the extraction unit turbines to provide power to drive the knifing, shredding, and dewatering machinery and to produce electricity in the turbo-generator. The process steam from the backend of the extraction unit turbines and turbo-generator is used to sustain the steam demands of the first evaporator effect, sugar drier air heater, and the deaerator. Meanwhile, a portion of the vapor from water evaporation in the multiple effect evaporators is extracted and used to sustain the vapor demands of the extraction, clarification, and crystallization unit. The vapor extracted from the evaporator unit is commonly termed vapor bleed in the sugarcane mills and likewise, this term is adopted for use in this dissertation.

2.1.1. Extraction unit

Figure 2-3 is a schematic diagram of a typical extraction unit consisting of a diffuser system. The equipment and stream tags and their respective descriptions are provided in Table 2-1.

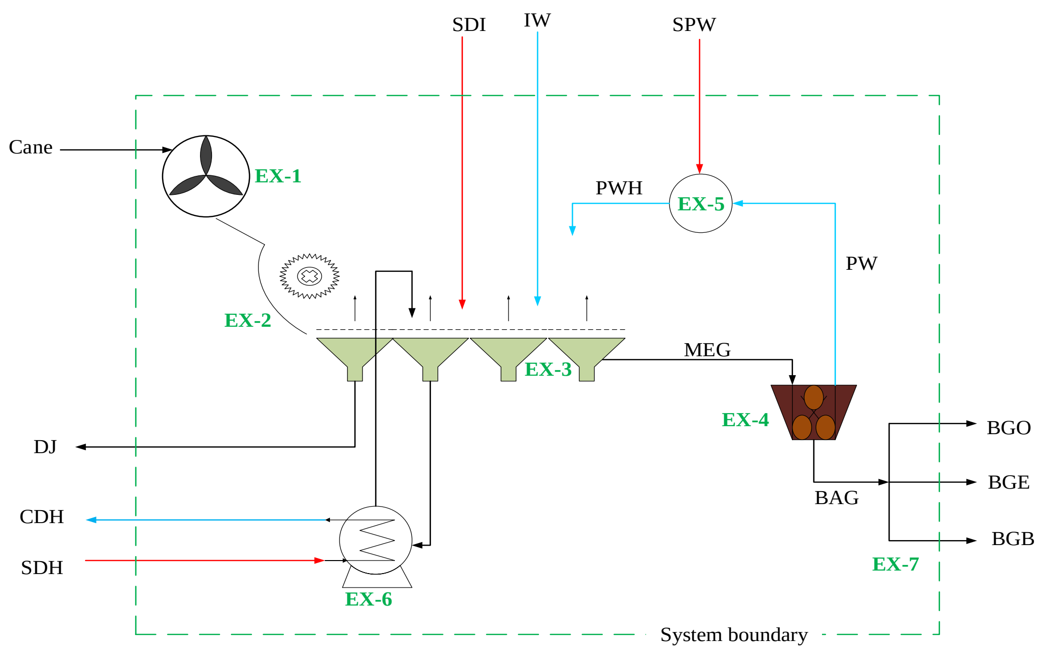

Figure 2-3: Process flow diagram of an extraction unit with knifing (EX-1), shredding (EX-2), diffuser system (EX-3) with the heating of recirculating juice(EX-6), dewatering mill (EX-4) with a preheater (EX-5) of the compressed juice(PW).

Table 2-1: Equipment and stream description for the extraction unit based on Figure 2-3

Equipment tag	**Equipment description**
EX-1 and 2	Cane knives and shredder
EX-3	Diffuser
EX-4	Dewatering mill
EX-5 and 6	Press water and juice heater
EX-7	Bagasse distributor
Stream tag	**Stream description**
BAG	Bagasse exiting dewatering mill
BGB	Bagasse directed to the boiler unit
BGE	Surplus bagasse
BGO	Bagacillo (fine bagasse particles)
Cane	Sugarcane
CDH	Condensate from the juice heater
DJ	Draft juice
IW	Imbibition Water
MEG	Wet bagasse
PW	Press water
PWH	Hot press-water
SDH	Vapor to the diffuser juice heater
SDI	Vapor injected into the diffuser
SPW	Vapor to the press water heater

This is the first process unit in the sugarcane mill operations and its objective is to extract as much sucrose from sugar cane as is possible and to ensure the fuel or calorific value of bagasse (BGB) for the boiler unit (BGB) is high by reducing its moisture content. Sugarcane knifing (EX-1) [1] and shredding (EX-2) [2] is first done to open the sugarcane cells, thereby facilitating the extraction of sucrose in the diffusers or milling tandems. Excessive shredding leads to the pulping of the cane fiber bed, which leads to reduced percolation rates in the diffuser and fiber conveying difficulties through the succeeding stages of the extraction unit [2]. Therefore, a balance is required between good preparation and excessive preparation. Extraction by milling tandems has always been the conventional method of processing cane, but over the years extraction by diffusion has become a preferred alternative [3]. The advantages of the diffuser over the mill are the higher extraction rates achieved, and their low capital and maintenance costs [3].

A diffuser (EX-3) is a carrier tank through which a bed of shredded cane is conveyed, while imbibition water and juice percolate through the fiber bed and the perforated slots of the conveyor [3]. The water washes out the sucrose from the cane and the juice thus formed is collected in a hopper and pumped to the next distributor, so that the juice moves backward from the bagasse discharge end to the cane entry end. This phenomenon is known as counter-current diffusion and helps to ensure minimal sucrose loss in the exiting bagasse stream [3]. The imbibition water (IW) added to the diffuser comes primarily from the evaporation unit, with additional amounts coming as condensate from the clarification and diffuser heaters [4]. Temperatures slightly over 80˚C are aimed throughout the diffuser to promote sucrose extraction and eliminate sucrose losses due to microbiological action [4,5]. Therefore, to ensure adequate temperature control, three heating systems are used, namely direct vapor injection (SDI) to the cane bed, heating of the press water (PW), and the heating of the percolating juice towards the cane entry side (EX-6). The final juice from the diffuser is termed draft juice (DJ) and it exits the diffuser at temperatures of about 65 ˚C [4].

The quantity of the bagasse is determined by the fiber content of the cane [3], while the bagasse ash, dissolved solids (sucrose and non-sucrose), and moisture content define the calorific value of bagasse as a fuel in the boiler [6]. While the sucrose extraction efficiency in the diffuser detects the amount of sucrose lost in the bagasse stream, the dewatering mill is the machinery responsible for compressing the water out of the bagasse, thereby reducing its moisture content. Therefore, for increasing the calorific value of bagasse, efficient sucrose extraction from the cane fiber bed and adequate dewatering of the bagasse is required.

2.1.2. Clarification unit

The objective of the clarification unit operation is to remove non-sugars (organic and inorganic) to produce clear juice free of insoluble and suspended particles at minimum cost, residence time, and sucrose loss due to inversion. Sucrose inversion is the hydrolysis of sucrose, which is a disaccharide, into the monosaccharides, glucose, and fructose [3]. Figure 2-4 is a schematic diagram of a clarification unit with a mud filtration system. The equipment and stream tags and their respective descriptions are provided in Table 2-2.

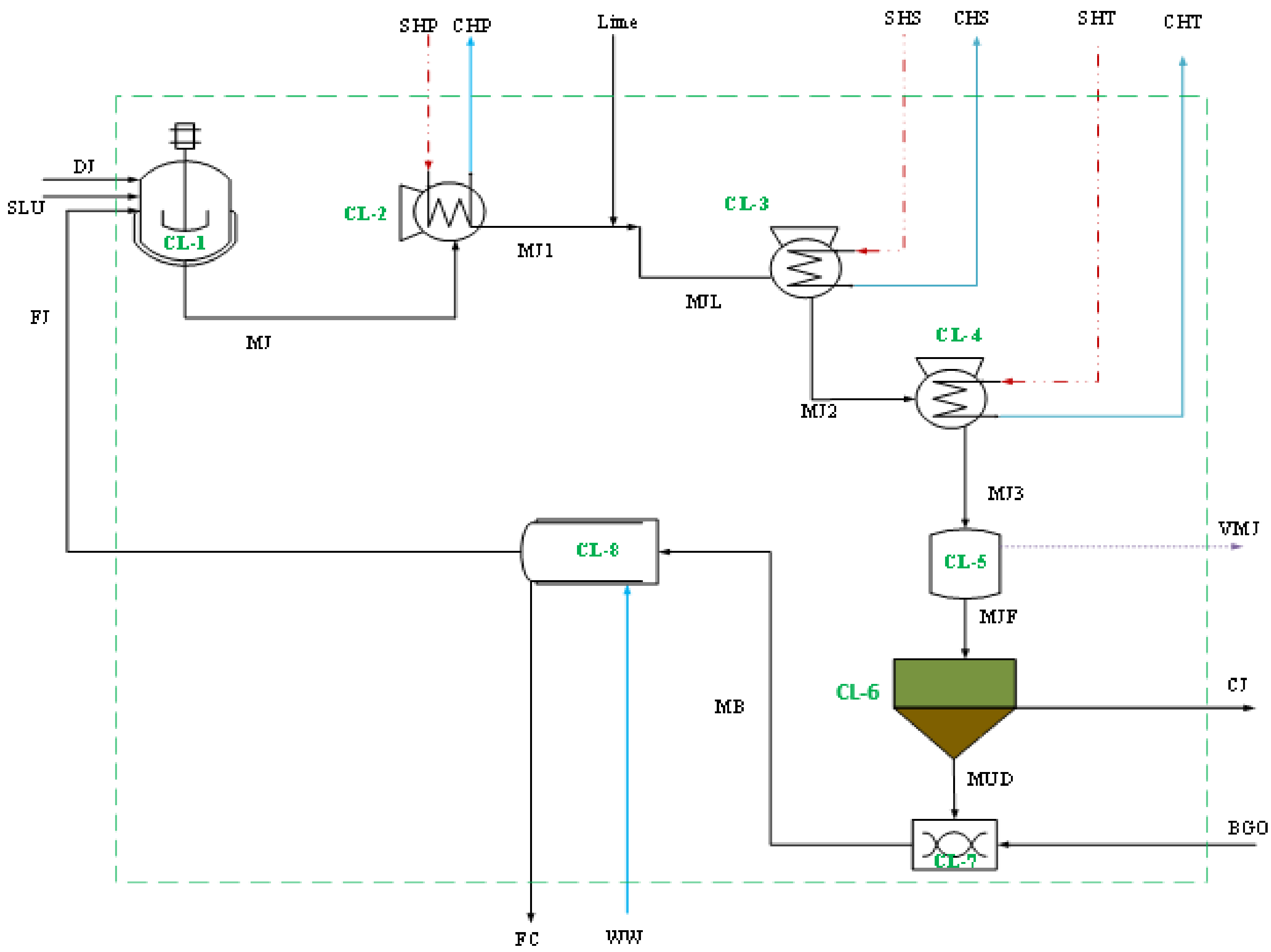

Figure 2-4: Process flow diagram of a clarification unit comprising of a mixing tank (CL-1), primary heater (CL-2), secondary heater (CL-3), tertiary heater (CL-4), flash tank (CL-5), clarifier (CL-6), blender (CL-7) and vacuum mud filter (CL-8).

Table 2-2: Equipment and stream description for the clarification unit based on Figure 2-4

Equipment tag	**Equipment description**
CL-1	Mixed juice tank
CL-2 to 4	Primary, secondary, and tertiary heat exchangers
CL-5	Flash tank
CL-6	Juice clarifier
CL-7	Blender
CL-8	Vacuum filter
Stream tag	**Stream description**
CHP, CHS, and CHT	Condensates from primary, secondary, and tertiary heaters, respectively
CJ	Clear juice

FC	Filter cake
FJ	Filtrate juice from mud filter
Lime	Milk of lime
MB	Vacuum filter feed
MJ	A mixture of DJ, SLU, and FJ
MJ1	MJ from the primary heater
MJ2	MJ from the secondary heater
MJ3	MJ from the tertiary heater
MJF	MJ from the flash tank
MJL	MJ with lime added
MUD	Settled mud from the clarifier
SHP, SHS, and SHT	Vapor to primary, secondary, and tertiary heaters, respectively
SLU	Sludge from thick juice filter
VMJ	MJ flash vapor
WW	Wash water to the vacuum filter

The draft juice (DJ) exiting the extraction unit is mixed with the juice filtrate (FJ) from the vacuum filter and the sludge (SLU) from the syrup filter [7]. The mixed juice is heated in a train of heat exchangers (CL-2-4) (primary, secondary, and tertiary heat exchangers), where vapor bled from the evaporator station is used for heating. Cold, warm, intermediate, or hot addition of milk of lime is done to maintain the juice pH slightly above 7 [3]. For further details of the different liming procedures in sugar factories, the reader is referred to the work by Doherty et al. [8]. Intermediate liming is commonly adopted in the sugarcane mills [3]. In intermediate liming, the mixed juice is heated in the primary heater (CL-2) before the inline addition of the milk of lime [3]. Achieving the desired pH for the clear juice is crucial for minimizing sucrose inversion losses in the subsequent evaporation stages [3]. The mixed juice with lime (MJL) is further heated in the secondary (CL-3) and tertiary heaters (CL-4).

Mixed juice is heated to above the juice boiling temperatures in the tertiary heater to ensure effective flashing (CL-5) of the dissolved gases, which if not removed would otherwise prevent the settling of suspended solids in the clarifier (CL-6) [8]. However, a balance is required because the higher the temperature of the juice after the tertiary heater, the higher the energy lost in the flash vapors exiting the flash tank [13]. Juice clarification takes place in the clarifier (CL-6) and the resultant clear juice is directed to the preheater in the evaporator unit, while the mud is fed into the vacuum filter (CL-8). Mud to the vacuum filter is blended with fine bagasse particles (bagacillo), which are used as a filter aid. The amount of bagacillo (BG0) used depends on the mud solids content, which is a result of soil intake in the incoming cane. Wash water (WW) is added to the vacuum filter (CL-8) to wash away as much sucrose as possible from the filter cake (FC). Although this strategy is beneficial in ensuring high sucrose recovery rates, this comes at the expense of increased energy demands in the factory to evaporate this additional water in the subsequent operational stages.

2.1.3. Evaporator unit

Figure 2-5 is an illustration of a typical evaporator unit system in a sugarcane mill. The equipment and stream tags and their respective descriptions are provided in Table 2-3. The stream tags and description for the vapor extracted in the evaporator unit are provided in their respective units in which they are used.

Table 2-3: Equipment and stream description for the evaporation unit based on Figure 2-5

Equipment tag	**Equipment description**
EV-1	Clear juice pre-heater
EV-2 to EV-6	5-Effect evaporator unit
EV-7	Thick juice filter
EV-8	Barometric condenser
EV-9 and 10	Condensate flash pots and tank
Stream tag	**Stream description**
C1-C5	Condensate from all effects
CEH	Condensate from CJ preheater
FV2-FV5	Vapor from condensate flashing directed to 2nd to 5th effect
L0	Preheated clear juice
L1-L5	Juice from all effect
M	Coldwater to the barometric condenser
S1	LP steam to the 1st effect
S2-S4	Vapor to 2nd – 4t^{h} effect
SEH	LP steam to the CJ pre-heater
SYR	Filtered thick liquor or syrup
V1	Vapor from 1st effect
VE2-VE5	Vapor from 2nd to 5th effect plus vapor from condensate flashing (FV2-FV5).
W	Warm water from the barometric condenser
WBF	Boiler feedwater
WEC	Exported water

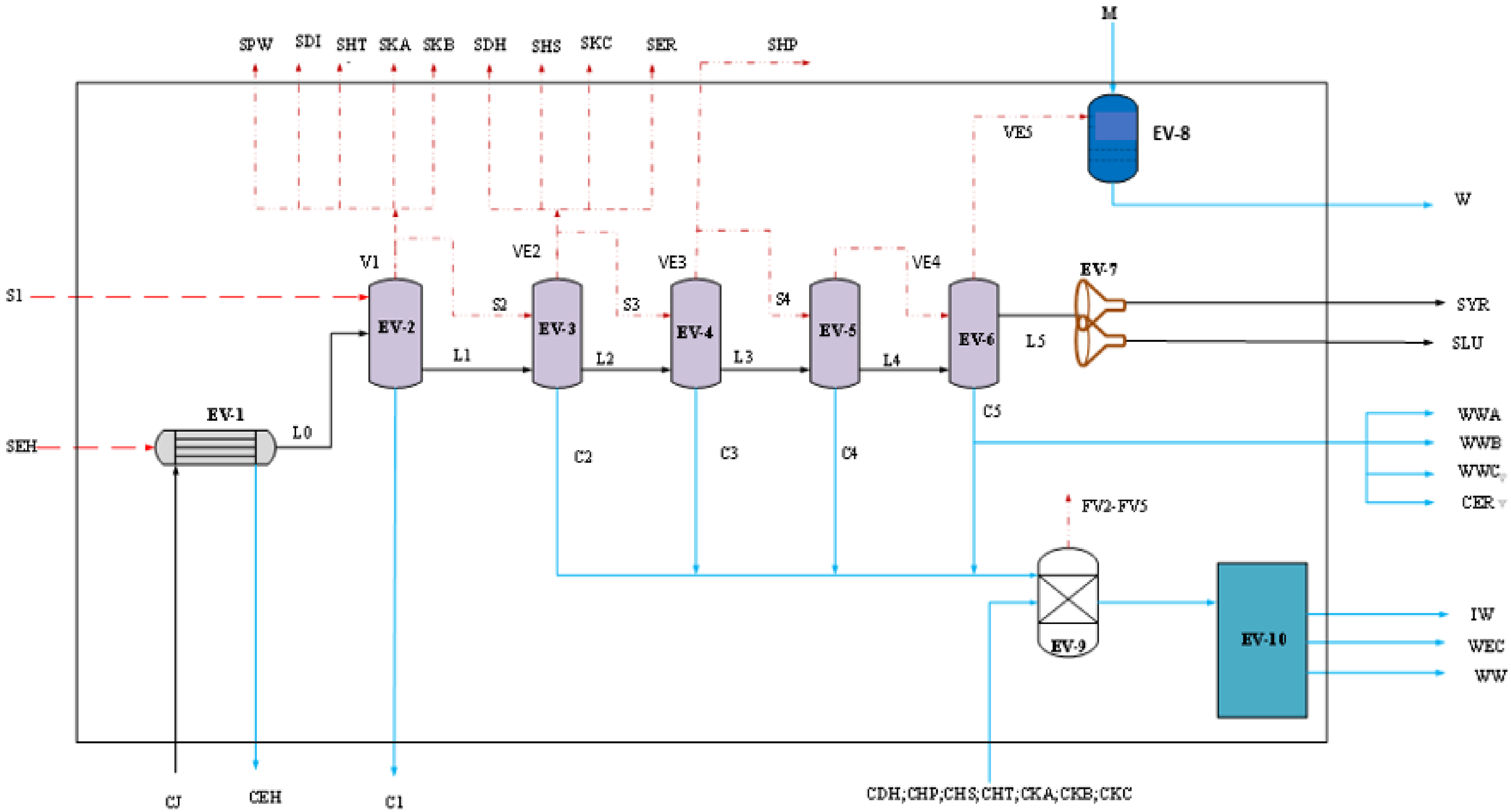

Figure 2-5: Typical evaporator unit in sugarcane mills with a preheater (EV-1), 5 effects (EV-2 to 6), a syrup filter (EV-7), and barometric condenser (EV-8)

Preceding the multiple-effect evaporators (EV2-EV6) is the clear juice heater (EV-1), which is used to raise the temperature of the clear juice to allow flashing to occur upon entry to the first effect (EV-3) [3]. An evaporation unit is an essential unit in the sugar factory as it is responsible for the concentration of the juice from around 13 to 68 % dissolved solids (DS) content [3]. Theoretically, the limit on the DS content of syrup is about 72% at which point crystallization commences [3]. However, due to measurement errors, in practice, a leeway of two units is given on the final syrup concentration to avoid the crystallization of the syrup in the storage tank as well as possible pumping problems [3]. Because of the high latent heat of vaporization of water and the amount of water to be evaporated, the evaporation unit is energy-intensive.

However, the steam economy of the evaporator unit is improved through the re-use of the vapor from water evaporation in each effect for the successive evaporations and extraction of a portion of this vapor (vapor bleeding) for use in the extraction, clarification, and crystallization unit [5]. The efficiency attained by the application of the multiple effect evaporators is the reason for the prospect of the sugarcane mills to not only generate all the steam and electricity it requires by burning bagasse but also to have the potential of producing surplus bagasse for valorization. However, the operational inefficiencies of the process units that are linked to the evaporator unit through vapor supply, lead to the inefficient operation of the unit [5]. Process vessels that operate under vacuum in the sugarcane mills mainly do so by using a barometric condenser system (EV-8) [3]. The main function of the condenser system is to create a vacuum inside the evaporator effects, thereby reducing the boiling temperatures of the juice and the sucrose inversion losses This successive reduction of the juice boiling temperatures in different evaporator effects allows for vapor from the previous effect to be used in the subsequent effect thereby reducing the energy requirements of the evaporator unit and ultimately saving on bagasse [3]. Although illustrated as one flash pot (EV-9) in Figure 2-5 for simplicity of the diagram, there are 4 condensate flash pots located at the outlet of each evaporator effect except for the first effect. The resultant flash vapors (FVE2-FV5) are returned to their respective effects to augment the vapor streams (V2-V5) from water evaporation.

2.1.4. Crystallization unit

Figure 2-6 is a process flow illustration of a typical crystallization unit in a sugarcane mill. The equipment and stream tags and their respective descriptions are provided in Table 2-4.

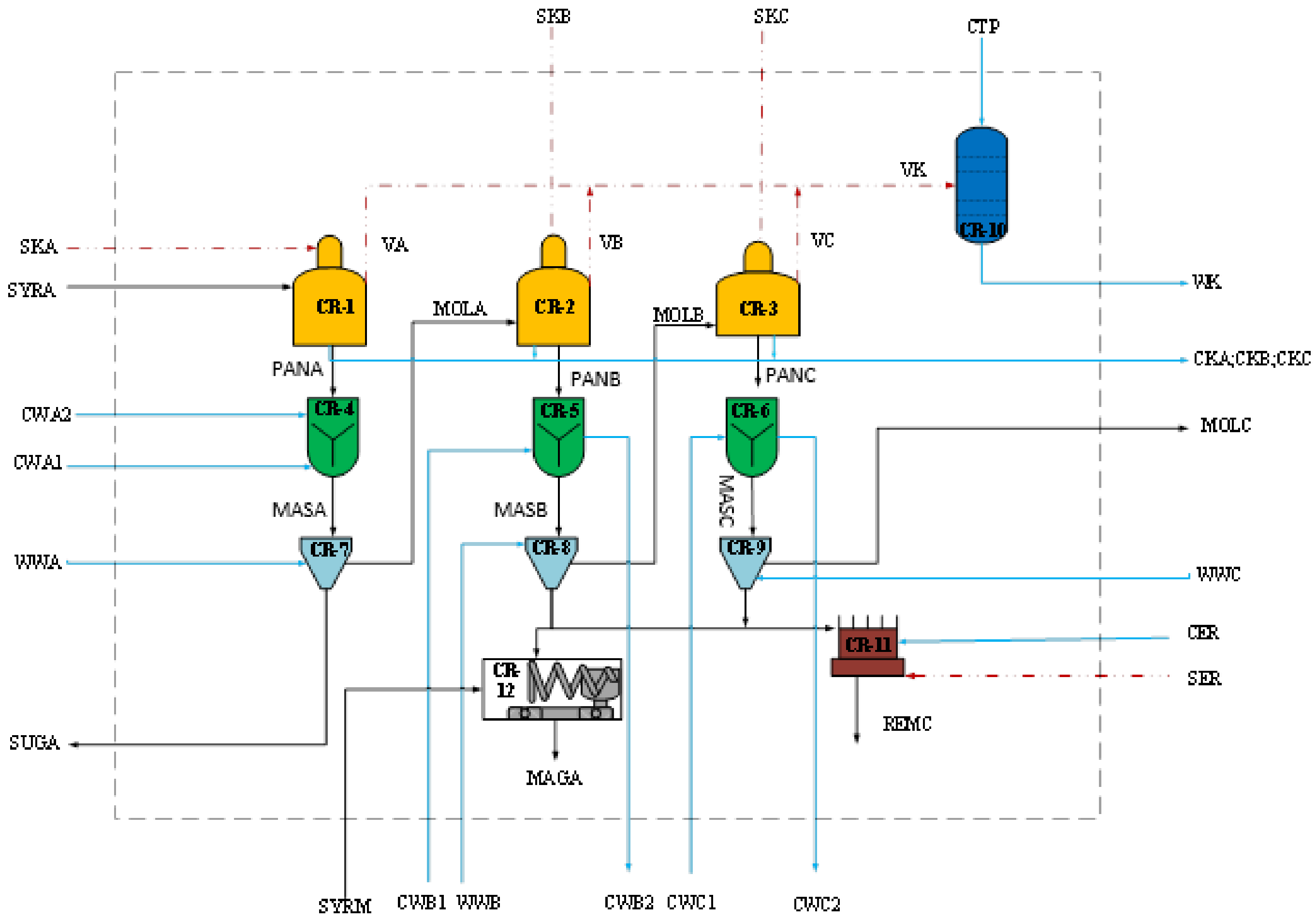

Figure 2-6: Process flow diagram of the crystallization unit with a 3-staged boiling scheme (CR1 to 3) and a re-melter (CR-11)

Table 2-4: Equipment and stream description for the crystallization unit based on Figure 2-6

Equipment tag	Equipment description
CR-1 to CR-3	A, B, and C vacuum pans
CR-4 to CR-6	Cooling crystallisers
CR-7 to CR-9	A, B and C centrifuges
CR-10	Barometric condenser
CR-11	Re-melter
CR-12	Mingler
Stream tag	**Stream description**
CER	Water to the re-melter
CKA, CKB, and CKC	A, B, and C-pans condensate
CTP	Water to condenser

CWA1, CWB1, CWC1	Water to cooling crystalliser
CWA2, CWB2, CWC2	Water from crystallisers
MAGA	Magma to A-pan
MASA, MASB, and MASC	A, B, and C massecuite from the cooling crystallizers
MOLA, MOLB, and MOLC	A, B, and C molasses
PANA, PANB, and PANC	A, B, and C massecuite from the boiling pans
REMC	Re-melted stream to A-pan
SER	Vapor to re-melter
SKA, SKB, and SKC	Vapor to A, B, and C-pans
VK	Vapor from A, B, and C pan
WWA, WWB, and WWC	Centrifuge A to C wash water
WK	Water from condenser

The sucrose content in the final residue of the crystallization unit referred to as molasses, must be as low as possible, since any sucrose left in the stream is a loss in sugar yield. In meeting this objective, the operation of the unit needs to be done in a way that the production targets are attained at minimal vapor usage. Hence the crystallization process is usually divided into three stages, to minimize the sucrose content in the molasses [3]. Furthermore, two types of crystallization processes are practiced in the sugarcane mills, namely the evaporative crystallization in the vacuum pans (CR-1 to 3) and cooling crystallization in the cooling crystallisers (CR-4 to 6) [3].

The syrup from the evaporator unit is directed into the A-pan (CR-1), while a small portion is extracted for use in the mingler (CR-12). The mingler combines the syrup with the B-sugar to produce a slurry of fine sugar crystals (MAGA), while the C-sugar is dissolved in the remelter (CR-11) [3]. The resultant slurry of fine sugar crystals and re-melted sugar are also fed into the A-pan to aid the sucrose crystallization process. Crystallization in the three vacuum pans continues until the maximum concentration of massecuite (a mixture of syrup and sugar crystals) is achieved. Massecuite leaving the vacuum pans is at temperature ranges of 63˚C to 70˚C [3]. At the outlet of each vacuum pan, there is a cooling crystalliser, which is used to cool the massecuite and ensure further crystallization.

Once the syrup forming part of the massecuite is exhausted to the practical limit, it remains only to separate the crystals from the remaining syrup. This separation of syrup from the crystals is done using centrifuges at the outlet of each cooling crystalliser. Centrifuges utilize centrifugal force and washing water or steam to drive out the syrup from between the sugar crystals [9]. The A, B, C sugars from the centrifuges are directed to the sugar drying unit, mingler, and re-melt, respectively [4,7]. The liquid stream (molasses) from the A and B centrifuge is recycled to the subsequent pan stages to ensure maximum sucrose recovery, while the C-molasses exits the factory [4,7]. The barometric condenser (CR-10) is used to create a vacuum inside the pans, thereby reducing the boiling temperature of the massecuite and vapor demands (SKA, SKB, SKC, and SER) from the evaporator unit.

2.1.5. Sugar drying unit

Figure 2-7 is a process flow diagram of a typical sugar drying and cooling scheme. The equipment and stream tags and their respective descriptions are provided in Table 2-5. Drying is the last process unit in the production of raw sugar. The purpose of the drying process is to reduce the surface moisture content and temperature of the commercial A-sugar. In addition to meeting the customer specifications, drying prevents the microbiological degradation of sucrose [3]. A portion of the air (DAI1) is directed to an air heater that uses LP steam (EXSS) before being passed to the drier. The hot air is used to heat up and reduce the moisture content of sugar from the A-pan (SUGA) while the cold air is used to cool the sugar to final temperatures of 35 ˚C [4,7]. The cooled and dried sugar exiting the drier (SUA) is transported for packaging using a conveyor belt. The air and steam requirements in the sugar drier depend on the efficiency of heat transmittance in the drier and the water content of the A-sugar coming from the A-centrifuge. The air heater in the sugar drier receives steam supply from the turbines and turbogenerator, while the boiler uses the resultant condensate from the heater as part of the feedwater.

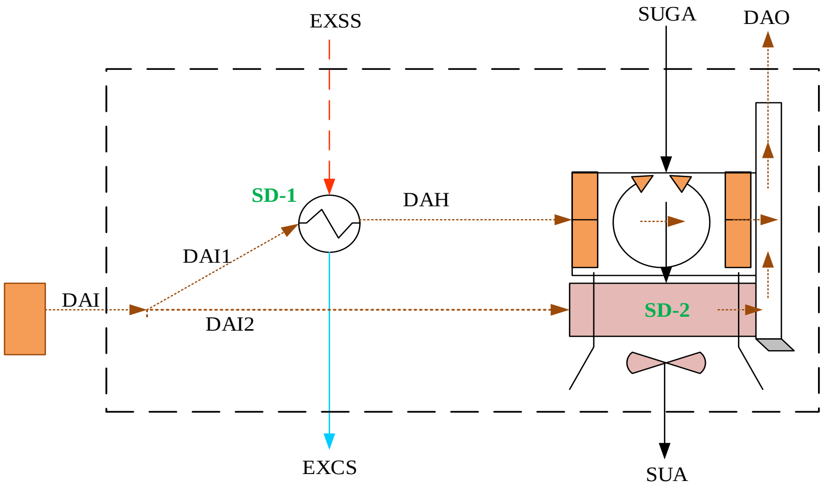

Figure 2-7: Process flow diagram of the sugar drier with an air heater (SD-1) and a sugar drying and cooling system (SD-2) which uses heated air (DAH) and DAI2, respectively

Table 2-5: Equipment and stream description for the sugar drying unit based on Figure 2-7

Equipment tag	**Equipment description**
SD-1	Air heater
SD-2	Rotary sugar drier and cooler
Stream tag	**Stream description**
DAH	Heated air
DAI	Air to sugar drying unit
DAI1	The air into air heater
DAI2	Air into cooler
DAO	Hot air exiting the drier
EXSS	LP steam to the air heater
EXCS	Condensed LP steam
SUA	Dried and cooled sugar
SUGA	A-sugar from the A-pan

2.1.6. Boiler and turbogenerator

Figure 2-8 is a process flow diagram of a typical steam and electricity generation system in sugar mills. The equipment and stream tags and their respective descriptions are provided in Table 2-6. The boiler unit and turbogenerator provide the steam and electricity requirements of the factory, respectively. Bagasse is incinerated in the boiler unit (UT-2) to generate high-pressure (HP) steam. If the bagasse energy is inadequate to meet the sugar mill's energy requirement, then it is supplemented using alternative fuels like coal or wood waste [3]. The typical modern water-tube boilers in the sugarcane industry are designed to burn bagasse, coal, or a mixture thereof [10]. The turbines convert the enthalpy of the HP steam to drive the machinery in the extraction unit (UT-4 to 6) and to generate electrical energy in the turbo generator (UT-3). The LP steam from the back end of the turbines is a source of thermal energy for the clear juice preheater, 1st evaporator effect, sugar drier, and deaerator [3]. The LP steam condensate from the evaporator unit and sugar drier is used as boiler feedwater (WBF) and any shortfall is sustained by the cold water (WBM) [3]. The LP steam provided to the deaerator (UT-1) offers the physical stripping action, while simultaneously heating the return condensate and cold makeup water to the saturation temperature before entry to the boiler unit [3].

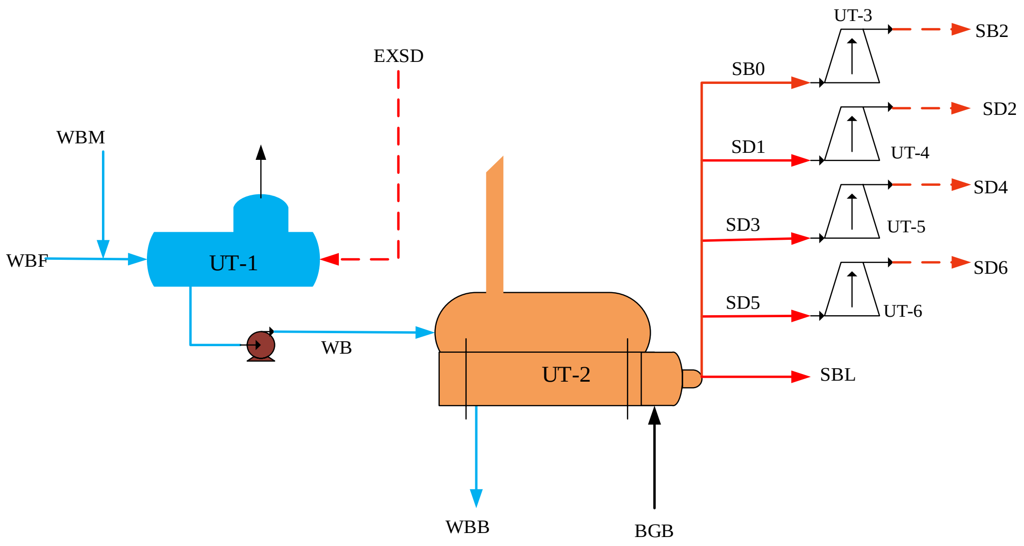

Figure 2-8: Process flow diagram of a deaerator (UT-1), boiler (UT-2), turbo-generator (UT-3), and extraction unit steam turbines (UT4-6)

Table 2-6: Equipment and stream description for the utilities (boiler, turbogenerator, and cooling tower) based on Figure 2-8 and 2-9

Equipment tag	**Equipment description**
UT-1	Deaerator
UT-2	Boiler
UT-3	Turbogenerator
UT-4 to UT-6	Extraction unit steam turbines
UT-7	Cooling Tower
Stream tag	**Stream description**
CTV	Cooling tower vapors
CTW and CWW	Total water from and to the cooling tower
EXSD	LP steam to deaerator
SB0 and SB2	HP and LP steam in UT-3
SBL	Sundry and losses HP steam
SD1, SD3, and SD5	HP steam to UT-4 to 6
SD2, SD4, and SD6	LP steam from steam turbines
WB	Boiler feedwater
WBB	Blowdown water
WBF	Returned condensates
WBM	Cold make-up water

2.1.7. Cooling tower

Figure 2-9 is a simplified representation of a cooling tower system. The equipment and stream tags and their respective descriptions are provided in Table 2-6. The objective of the cooling tower (UT-7) is to provide water at the right temperature for the cooling requirements of the plant. Evaporative heat dissipation occurs in the cooling tower as a small amount of water is evaporated into the moist air stream to provide significant cooling to the water being cooled [11]. As the cooling medium, it is crucial to the performance of the cooling tower to monitor the air variables. The wet-bulb temperature is the most important air variable as it strongly influences the moistness and enthalpy of air [11].

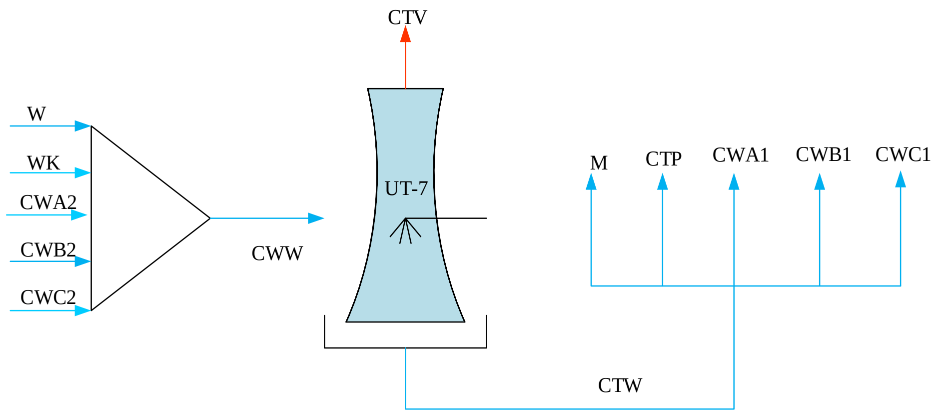

Figure 2-9: Schematic diagram of a cooling tower (UT-7) with CWW and CTW representing the total warm and cold water flows, respectively.

Cooling tower efficiency is defined as the ratio of the actual cooling range (the difference between hot and cold-water temperatures) and the ideal cooling range (the difference between hot water and wet-bulb temperature) [11]. When the wet-bulb temperature decreases it increases the potential of cooling the water to lower temperatures. However, depending on the control strategy used the effect of the wet-bulb temperature on the cooling efficiency has different interpretations. For an open-loop system, where the attained cold-water temperatures can vary with the wet-bulb temperature, a decrease in the wet-bulb temperature will result in lower cold-water temperatures. While for low wet-bulb temperatures this system might be beneficial, for high wet-bulb temperatures this can have adverse effects on the downstream processes utilizing the water. Hence a closed-loop system is preferred for industrial applications as considered here, which controls the cold-water temperature at a target set-point by manipulating the air to water ratio [11]. For such systems, the actual cooling range is maintained constant, while the ideal range varies with the wet-bulb temperature. For these reasons, low wet-bulb temperatures result in a lowered cooling efficiency as an indication that the cooling tower has more cooling potential that is not being utilized [11]. Such identifications and interpretations are crucial for finding potential areas for improvement. Furthermore, based on this discussion, the significance of interpreting a defined energy indicator value in conjunction with the control policies used is shown.

2.2. Sugar mill energy consumption

2.2.1. Energy consumption of unit operations

The processes involved in the direct manufacture of raw sugar from sugar cane are relatively simple. However, it is the complex interaction of the process units through feed and energy supply that defines the production and energy efficiency of a sugar mill. The unit operations used in the production of raw sugar consume electrical and thermal energy for crushing, pumping, evaporation, centrifugation, and drying purposes [12]. Sugarcane mills typically require 400–550 kg of HP steam per tonne of sugarcane, but, by using energy-efficient practices and state of the art technology, sugar manufacturing steam requirements can be as low as 280–300 kg-steam/ tonne of sugarcane [12]. The electricity consumption is often in the ranges of 24 and 32 kWh/tonne sugarcane crushed [13].

To establish an effective energy monitoring system for sugarcane mills it is necessary to identify the major energy-consuming or wasting unit operations whose monitoring and control would make a noticeable difference in the energy improvement efforts. Therefore, mass and energy balances around each process unit were conducted based on the data in [4,7] for a typical 250 tonnes/hr sugarcane mill with an HP steam consumption of 400 kg/tonne of crushed sugarcane. The results of the calculations, given by the mass and energy balances, were used to analyze the energy usage for a typical sugarcane mill, as a percentage of the energy available in bagasse with a moisture content of 51 % [4,7]. The results of the analysis are presented in Figure 2-10, for bagasse with a gross calorific value of 9 160 kilojoules per kilogram bagasse (kJ/kg).

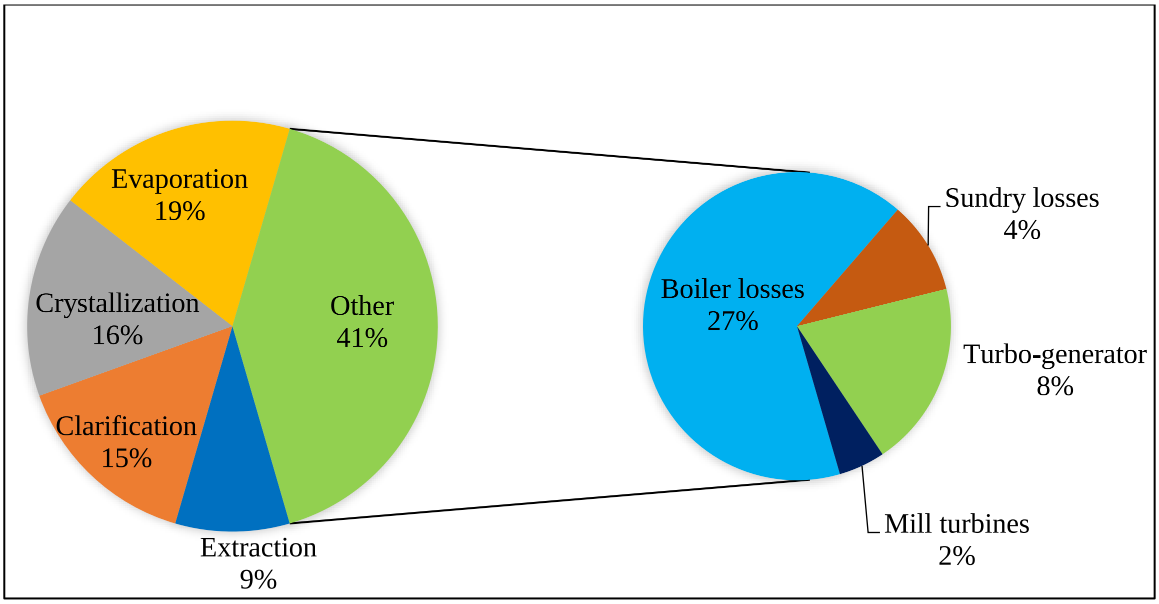

Figure 2-10: Operational units' percentage share of the bagasse energy content for a 250-tonnes of cane/hr sugarcane mill with an HP steam consumption of 400 kg/tonne of crushed cane [22]

Approximately 27 % of the energy in the bagasse fuel fed to the boiler exits through the flue gases, while 4 % is lost through the HP and LP steam sundry losses. The wastage of bagasse energy in the boilers can be reduced by increasing the calorific value of bagasse through reduction of its moisture, DS, and ash content or investment in more efficient high-pressure boilers. The energy required for the production units is about 59 % of the bagasse energy content, with the evaporation and crystallization unit comprising 35 % of this energy, thus making them the major energy-consuming process unit (Figure 2-10). The sugar drier unit only constitutes 0.013% of the bagasse energy content and for presentation in Figure 2-10, the bagasse energy usage portion of the sugar drying unit is combined with that of the crystallization unit. The energy consumption for the evaporation unit compares with the literature value of 17.3 % for an Australian sugarcane mill given by Lavarack et al. [14]. This shows that despite the use of multiple-effect operating principles and the vapor bleeding strategies, an evaporator unit is still an energy-intensive unit in the sugarcane mill. The vapor requirements of the heaters in the clarification and extraction unit constitute 15 and 9 % of the total bagasse energy, respectively. The extraction unit turbines take up 2 % of the total bagasse energy for the direct driving of the cane knives, shredder, and dewatering mill, while the electricity demands of the factory operations constitute 8 % of the bagasse energy.

Therefore, the boiler is the area for major energy wastage in a sugarcane mill, while the evaporator and crystallization units are the major energy-consuming units. Previous studies have advocated for new designs of the evaporator vessels [21] and the installation of higher-pressure boilers [14] to improve the energy efficiency of these process units. However, the expected benefits from new equipment designs can be compromised by the lack of adequate process monitoring and control while the high cost of such new equipment can make them unfavorably for investment. For adequate process monitoring and control, precise measurements are required. The installation of precise sensors when systematically done can lead to lower investment requirements compared to purchasing new equipment like higher pressure boilers or falling-film evaporators. Furthermore, to motivate energy conservation awareness and future investment in bigger projects like procuring new equipment Singh [17] recommends starting with the implementation of energy projects with small capital investments and high returns. For these reasons, the present study seeks to use the existing equipment in these units to improve energy efficiency through the installation of precise sensors for enhanced process monitoring and control. The proposed approach in this study can enable precise energy usage estimation in a manner that allows the cane sugar manufacturers to systematically identify the process units whose improved control needs to be augmented with the installation of new equipment.

Most of the operational aspects related to the evaporation and crystallization unit require a balance between maximum sugar production and minimization of energy (bagasse) usage. For such trade-offs to be possible, optimal plant-wide control strategies are required, which consider the value of sugar and the cost of lost opportunity through decreased surplus bagasse availability. However, in studies where such strategies are considered the fixed values of sugar and bagasse are assumed, despite the general acknowledgment of the volatile markets [15,16]. Therefore, the optimal control or design solutions from such studies are not robust enough for cane sugar manufacturers to use for compromising between minimizing energy usage and maximizing sugar production. Balancing between minimizing energy usage and maximizing sugar production is further restrained by the unavoidable variations of the external process disturbances linked to the sugarcane flow and composition variations. These elements must be considered in the formulation of control strategies, but there are no known studies that have evaluated the stochastic risks associated with the variations in the external disturbances and market prices for the steady-state plant-wide optimal control of sugarcane mills.

2.2.2. Causes of energy and economic inefficiencies

To identify the areas where major energy and economic improvements may be achieved, it is considered essential to first identify the prevailing causes of energy and economic inefficiencies in sugarcane mills. The overall objective of any cane sugar factory is to convert the input feedstock (sugarcane) into the desired product (raw sugar) using the available sources of energy economically. However, during its operation, a sugarcane factory must satisfy several requirements imposed by its design configuration and socio-economic conditions, in the presence of ever-changing external and internal influences or disturbances [15,17]. Based on the critical review of the available literature [15,17–20], factory visits, and analysis of the responses from the questionnaires distributed to the South African and Australian sugarcane mills, a cause and effect analysis was drawn up, as displayed in Figure 2-11. The questionnaire template drafted for distribution in the sugarcane mills is in Appendix A. The cause and effect analysis in Figure 2-11 shows the disturbances responsible for energy and economic inefficiencies in the sugarcane industry.

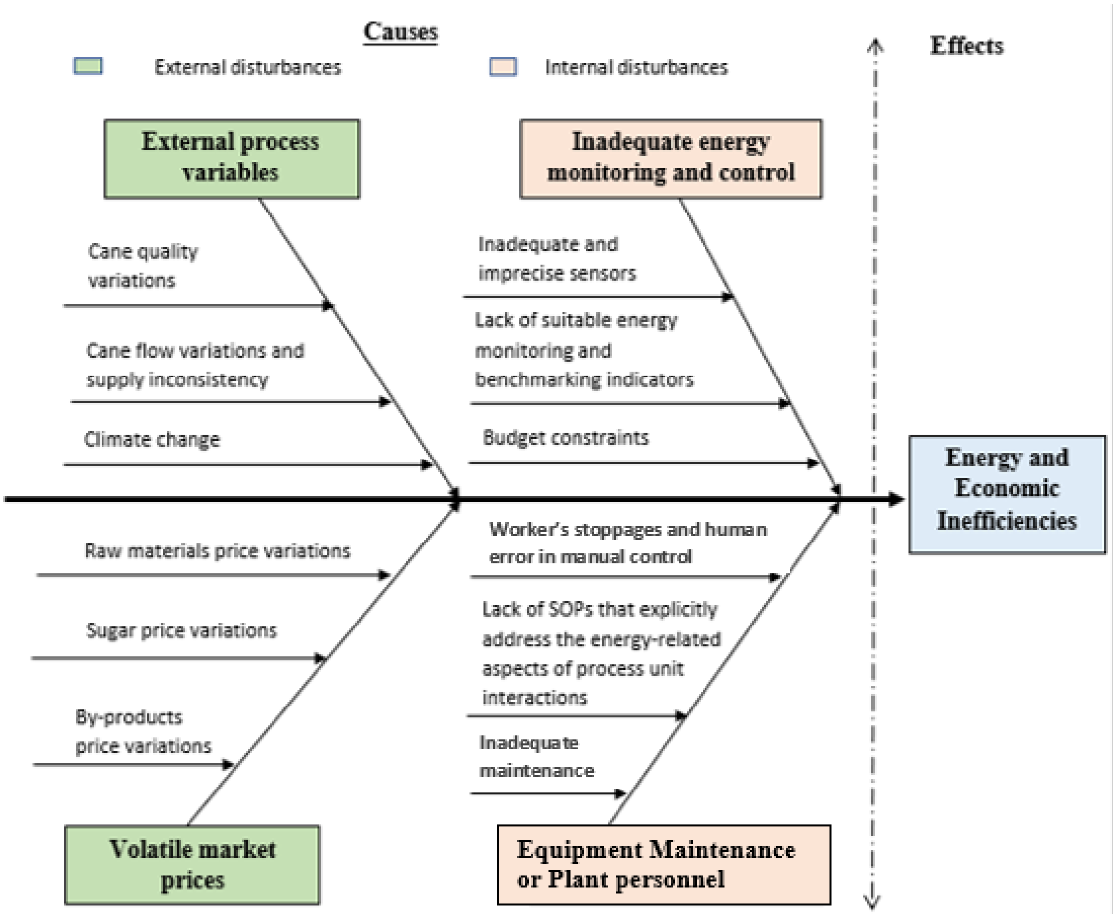

Figure 2-11: Fishbone diagram for the causes of energy and economic inefficiencies in a typical sugarcane factory

The external disturbances are due to outside variables that the sugar manufacturers have no control over [21,22]. The external disturbances are often associated with the inherent randomness of the process disturbances and market prices. Process disturbances compromise the steady-state control of the process operations, while the market price variations influence the plant-wide economics and lead to changes in the best strategies that can be used for balancing between minimizing energy usage and maximizing sugar production. For example, if the price of sugar is high and the bagasse price is low, the strategy can be to prioritize sugar production at the expense of excess energy expenditure. Sugarcane growth and harvesting issues result in random variations of the sugarcane composition and supply to the factory [21]. Increases in the sugarcane fiber and non-sucrose contents lead to reduced sugar production, due to increased bagasse and C-molasses quantities and their corresponding sucrose losses [3]. The calorific value of bagasse depends on its moisture, DS, and ash content [6]. Therefore, increased amounts of sucrose in bagasse due to high sugarcane fiber will reduce the calorific value of bagasse. These variations in the calorific value of bagasse compromise the ability of the boiler control system, whether manual or automatic, to maintain all process variables at levels that result in high efficiency.

On the other hand, internal disturbances mainly emanate from inadequate energy monitoring and control systems [17,19,22], and the manual control of certain operations, which can result in wrong operational decisions and compromised process control [18,22,23]. Energy monitoring and control are parts of an energy management system. Energy monitoring focuses on the visualization and evaluation of collected and saved data, thereby allowing for more transparency of the energy consumption trends in a factory that can save as a basis for comparison against specified energy indicator benchmarks. Hence suitable energy indicators must be defined for monitoring and benchmarking energy usage of the different factory operations. Energy control is done in addition to process and energy monitoring, and it describes the continual analysis and improvement of energy. Therefore, for energy monitoring and control to be possible, process measurements of the major energy flows or areas of potential energy improvements must be available. However, there is a lack of adequate instrumentation and imprecise measurements in sugarcane mills, which make it impossible to obtain precise energy estimations and transparency of the energy usage trends [17–20]. Cost constraints in the industry lead to reluctance to invest in instrumentation and advanced control systems for energy improvement and are therefore considered as some of the reasons for instrumentation problems in sugarcane factories [17,18,24]. Furthermore, cost constraints can lead to inadequate maintenance of process equipment thereby resulting in low overall equipment efficiencies.

With regards to addressing the energy monitoring challenges in sugarcane mills, Foxon et al. [22] recommended:

i. That the calculation of energy benchmarks should be based on variable inputs like the sugarcane composition.
ii. The allocation of areas of high energy use within the factory.
iii. The integration of these allocations with existing energy indicators and the translation of observations into the cost of lost opportunity

On the other hand, Rozsa [18] on the review of automation in the sugar industry states that:

"*The problem is that other subjects, which are important to the very survival of a plant are neglected. Instrumentation and automatic process control, plant-wide optimization, on-line (that is: real-time) quality control, to name only a few, are completely missing or are treated on an archaic level*".

Therefore, with regards to addressing the disturbances in Figure 2-11, while considering the expert reviews by Rozsa [18] and Foxon et al. [22], the sugar industry needs are classified as follows:

i. Suitable energy indicators that will allow for energy monitoring and targeting based on the variables or process activities that contribute to excess energy demands [17,19,20,22].
ii. A better understanding of the influence of the unavoidable disturbances on the factory operations and economics [17,22].
iii. Optimal plant-wide control and design solutions with scientific backing and not too rigid to apply in practice [16,25–29].
iv. Adequate and precise instruments for energy estimation and control [17–19].
v. Standard operating procedures to ensure uniform and efficient operation of the process units throughout all factory production shifts [17].

2.3. Review of energy management studies

Sugarcane mills use the energy from bagasse as fuel to produce HP steam, which is used in the extraction unit turbines and turbogenerators to produce power and process steam for the factory operations. Hence the historical fuel price markets had no direct effect on the industry and the sugarcane mills had no justification in the past to achieve higher energy efficiencies [30]. For these reasons, the production units required large quantities of steam, and boilers were inefficiently designed and operated to avoid the disposal costs of surplus bagasse [16]. Peacock and Cole [16] further argued that this strategy has resulted in sugar factories with relatively low capital costs and poor energy efficiencies. However, with the change in the economic and operational drivers of the sugarcane industry, there is growing interest among the global sugar manufacturers to improve energy efficiency and benefit from the additional revenue from surplus bagasse [9,30]. This section seeks to review the present progress in the energy management literature with regards to addressing the industry needs (Section 2.2.3) for improved energy and economic efficiency improvement in the sugarcane industry. A brief review of the applied strategies for other industries with energy-intensive operations is also done to assist in establishing the potential strategies and methods that can be used for the sugarcane industry.

2.3.1. Definition of suitable energy indicators

Energy indicators are tools used to quantify the energy performance of either the whole system or its various operational units [31]. Energy indicators can either be oriented to the micro-level, such that the process unit's inefficiencies are easily detected, or to the macro-level, for an overall factory energy consumption perspective [32,33]. The common definition of energy indicators is a ratio of the useful output in a system to the energy input to the system. Given the proliferation of literature on the potential of energy indicators in establishing a successful energy management system, questions concerning their definition and detail of disclosure have risen amongst sugar manufacturing industries and stakeholders [17,20,22]. This has been followed through with a definition of various energy indicators for use in energy monitoring of sugarcane mills [19,22]. Singh [17] provided a list of key variables for energy benchmarking, citing HP steam usage per tonne processed sugarcane as the commonly used index for overall-factory level energy consumption. The author [17] further reasons that this factory level index is more useful for internal benchmarking of the factory but lacks adequacy for external energy benchmarking as the cane fiber content differs from factory to factory.

Kinoshita [34] recommends an alternative factory level index for evaluating the net power generated in terms of the sugarcane fiber rate. This index provides a standardized manner to benchmark different sugar mills despite the sugarcane quality differences. Singh [17] comments on the limitation of this index in excluding sucrose-bearing streams (import and export), which are useful for quantifying production, energy, and financial losses. This is valid reasoning considering the financial implications of such streams from a production (loss of useful material) and energy (reprocessing/rework) viewpoint. However, it can be argued that finding a universal indicator that highlights all the energy aspects of a sugarcane mill can be hard. Therefore, a set of suitable energy indicators must be defined which when taken together provide a clear picture of the whole system including the existing energy interlinkages among the process units. Furthermore, while indices like the HP steam usage per tonne processed sugarcane may be essential for measuring energy performance, they do not provide adequate information about the areas of energy wastage such that operating solutions are implemented in a structured way.

While the common approach is to link energy usage to the production output, new approaches that relate energy usage to the most influential variables that can be controlled, have gained attention [35]. Sensitivity and statistical analysis are the preferred methods for these purposes [36–38]. This is often accomplished by evaluating the sensitivity of energy usage to the controllable variables (CVs) and statistically developing energy models that can be used for energy estimation and targeting based on these relevant CVs. ENERGY STAR, a US program for environmental protection, uses statistical analysis to develop energy indicators as functions of the contributing process activities in manufacturing industries [39,40]. These strategies have been applied in the monitoring and benchmarking of energy-intensive operations in the pharmaceutical [41], cement [42], and paper and pulp industries [43]. The use of energy indicators forms a basis for plausibility checks on available control systems and new potential control strategies while allowing for constructive dialogue among plant personnel in interacting process units on possible energy improvement strategies. This is especially pertinent for sugarcane mills owing to the complex interaction and dependence of the different operational units. However, a gap was identified in the research area relating to the statistical development of energy indicators based on influential variables that can be controlled in sugarcane factories.

2.3.2. Monte Carlo analysis

The external disturbances associated with the inherent randomness of the external process variables and market prices lead to energy and economic inefficiencies in sugarcane mills. Therefore, a need arises to have comprehensive knowledge of the effect of external process variables and market price variations on the steady-state operation and economics of a sugarcane mill [21,22,44]. Such knowledge can assist sugar manufacturers to balance between reducing energy usage and maximizing sugar production. However, the approaches that are often used to model the sugarcane mill operations assume fixed or seasonal-averaged values for these unavoidable disturbance variables [21,44]. This obscures the reflection of the real-life factory behavior under the inherent random variations of these external disturbances.

Monte Carlo simulations provide an approach to include uncertainty in the model predictions by randomly sampling from the probability distributions of the input disturbance variables, which show their real-life variation [45]. A sensitivity analysis using Monte Carlo helps to determine the stochastic effects of the random disturbances and to identify the disturbances with the largest impact on the factory operation and economics [46]. Moreover, unlike the conventional sensitivity analysis strategies, the use of the Monte Carlo approach allows one to capture the probability of two or more disturbances occurring at the same time. Although Monte Carlo simulation has been extensively used in contemporary science [47], finance [48], and engineering [45], there is limited application of this technique in the sugarcane mill-related studies, with the work by [21,44] being a noticeable exception. Studies by [44] applied Monte Carlo to evaluate the technical and economic viability of a cogeneration project for a sugarcane mill aimed at exporting renewable electricity under the random variations of sugarcane flow, sugarcane fiber content, and relevant market prices. Sharma and Peacock [21] used Monte Carlo to evaluate the impact of random variations in sugarcane flow and sucrose content on the vapor supply and demand view of a sugarcane factory when the last evaporator effect is operated at a pressure of 0.35 compared to 0.15 bar.

The fiber content of sugarcane has an influence on sucrose extraction, such that if the fiber content is high, then there is an increase in bagasse production and a corresponding increase in sucrose loss [3]. From an energy outlook, although this might lead to increased bagasse quantities, the corresponding increase in its sucrose content lowers the calorific value of bagasse as a fuel in the boiler, thereby prompting the need for increased bagasse flow to the boiler [3]. Hence the effect of the sugarcane fiber has an impact on the sucrose extraction efficiency in the diffuser and the boiler efficiency. For these reasons, it is considered important to evaluate the effect of the external disturbances and market prices from a plant-wide perspective, such that the different impacts of the disturbances in various operations are assessed. This kind of evaluation is especially pertinent for the sugarcane factories considering the intricate interaction of the process unit operations. While climate change is often addressed with regards to its impact on the sugarcane availability and composition [49–52], the impact of the changes in air temperature and relative humidity, also need to be evaluated, since air is used for the sugar drying, boiler, and cooling tower unit operations. Therefore, despite the notable works by [21,44], there is scope to consider more disturbances and to evaluate the combined steady-state effects of the process disturbances and market price variations on plant-wide control and economics of a sugarcane mill.

2.3.3. Optimal control and design solutions

Despite the general acknowledgment that there are frequent and random variations in the external disturbances in sugarcane mills, optimization focused studies often assume fixed values for these variables [16,29,53,54]. Consequently, important system trends can be missed, and the resulting design or control solutions are only optimal for the disturbance values used and leave the factory operations vulnerable to their stochastic nature [4]. Therefore, there is scope to develop optimal control solutions that are robust and resilient to the variations in the unavoidable disturbance variables. Following this reasoning, in recent years there has been an increasing interest by both academia and industry to use strategies like model predictive control [55,56] and set-point optimization [57–60] to ensure optimal factory operation.

Model predictive control (MPC) is an advanced method of process control that relies on the use of an accurate dynamic model to control a process while satisfying a set of constraints. Due to the complexity of modeling the dynamics of certain processes, data-driven performance assessment approaches have gained popularity [61–64]. The MPC strategies have been used for the optimal operation of oil refineries, evaporators, and many more applications [55]. The main advantage of MPC is that it allows for the optimization of the present time slot while considering the anticipated trends for the next time slot [55,56]. On the other hand, set-point optimization uses a steady-state model to recompute the optimal set-points for the CVs regularly, based on the frequency of variation of the external and unavoidable disturbances [60]. The re-calculating of the new optimal set-points can be done online or offline on an hourly or daily basis. Both MPC and set-point optimization use an economic index to define the optimality of operation. Steady-state models that describe the entire mass and energy balances of the sugarcane mill operations are available [7,65,66]. However, there are currently no commercial dynamics models that describe the entire sugarcane mill operations and there are inadequate data measurements or estimates for using data-driven approaches.

In this regard, despite the advantages of MPC, set-point optimization provides a simpler and readily implementable strategy for sugarcane mills to improve their operation using the available steady-state models of the entire sugarcane mill operations. Set-point optimization has been used to improve the operational economics of wastewater treatment plants [59], fermentation processes [57], distillation plants [60], and chemical reactors [67]. Set-point optimization can be done either online or offline. There are no known studies that have investigated plant-wide set-point optimization as a strategy for maintaining optimal steady-state operation and economics of the sugarcane mill operations in the presence of external disturbances. Hence there is a need to evaluate the benefits of using set-point optimization to improve the steady-state operation and economics of a sugarcane mill. The requirements for setting up set-point optimization based on the Monte Carlo approach are:

i. Definition of the scalar objective function to be minimized or maximized for example maximizing the net-revenue of a factory.
ii. Process model formulation or selection.
iii. The collection of information relating to the external disturbances and the use of the data to estimate their probability distributions.
iv. Selection of the CVs that the optimizer uses to maximize the revenue by finding their new optimal set-points for the given external disturbance information. The criteria used for selecting the CVs is their envisaged role in improving the plant-wide factory economics.
v. Definition of the feasible operating regions to guide and ensure the attained optimal set-points do not violate the factory related operating, safety, and product quality constraints.
vi. The selection of an optimization algorithm to use to compute optimal set-points that the controller attempts to implement for improved plant-wide economics. Figure 2-12 illustrates the differences between a global and local optimum solution of an objective function. A global minimum solution is when the objective function value is smaller than or equal to the value of all the feasible points of the problem. On the other hand, a local minimum is a point where the objective function value is smaller than the nearby points but with the possibility of being greater than distant points as shown in Figure 2-12. To obtain global optimum solutions for an optimization problem that can contain multiple local minima or maxima solutions, the use of a global optimization algorithm is recommended.

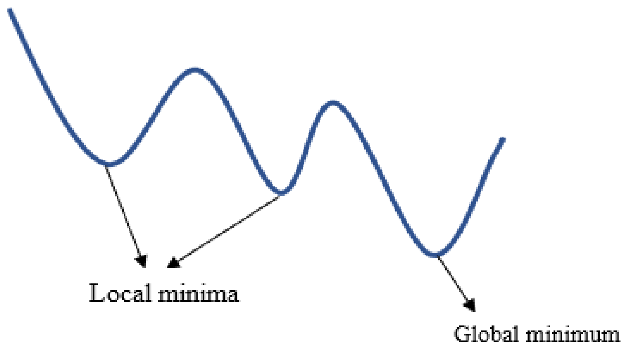

Figure 2-12: Illustration of the differences between local and global optimum solutions Of an objective function with many local minima points

There are different global optimization algorithms available like pattern search, surrogate, and genetic algorithms [68]. Pattern search has a proven convergence to local optimum and can handle all types of constraints. While surrogate optimization converges to a global solution but can only handle bound constraints [68]. Although genetic algorithms (GAs) can handle all types of constraints, there are convergence problems for non-smooth optimization problems [68]. Each solver possesses different search characteristics; hence it is considered essential to select a solver that is best tailored for the defined optimization problem.

2.3.4. Process measurements and control

Energy monitoring is founded on the axiom "you cannot manage what you cannot measure" [69]. Therefore, to establish a successful energy monitoring strategy, the measurements of the variables that can be controlled need to be available. Furthermore, these measurements should provide accurate and precise readings of the CVs to ensure correct estimation of the factory performance and formulation of control solutions [70]. A precise sensor provides a high degree of agreement among consecutive measurements of a fixed variable value [70]. The use of precise measurements and subsequently improved control makes it possible to move the steady-state operation of the factory closer to the operating constraints, which typically harbor significant energy savings and profits [71].

This notion is illustrated in Figure 2-13 with an example of syrup DS content measured by two instruments with differing precision. It is generally acknowledged that operating at higher syrup DS content (close to 72) is beneficial for energy improvement and factory economics. However, if one sensor provides a standard deviation of 10 from the actual value, then the set-point for syrup DS needs to be restricted to 62 to avoid the violation of the operating constraint. Meanwhile, the use of a more precise sensor with a standard deviation of 2, allows for the evaporator operations to be operated at syrup DS content closer to the operating limit, which garners more profits and energy savings.

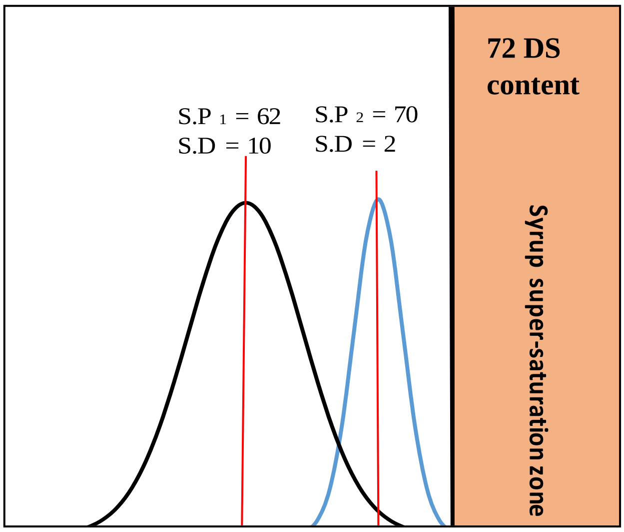

Figure 2-13: Role of precise measurements in pushing the envelope of operation closer to the operational constraints

However, the lack of adequate and precise instrumentation is reported as one of the barriers to effective energy monitoring in sugarcane mills [17,19,72]. The cost of purchasing sensors for a factory tends to rise with an increase in the number and the precision of the sensors. Budget constraints in the sugarcane industry result in resistance to invest in technology or systems envisaged to improve the energy efficiency of the factory operations [72]. Singh [17] states that the sugarcane industry requires energy monitoring projects with high payback rates to create a climate of success and motivate major investment projects. To enhance investing confidence, the selection of measurements must be made by evaluating both the required instrumentation cost and the economic benefit to the factory. Sensor network design procedures are conducted to address a specific process activity like fault detection or process monitoring and control [73]. For fault detection, sensors are selected for identifying and resolving faults [74]. The common approach to the cost-based design of sensor networks is based on the cost of purchasing the measuring instruments [73], with sensor specifications for reliability, accuracy, or precision. On the other hand, Nguyen and Bagajewicz [75] recently introduced a method for evaluating the economic effect of maintenance policies on installed factory sensors [75]. In recent years there has also been an increase in studies that use profit-based evaluations for sensor network design [70]. Profit-based evaluations are easy to interpret and of direct use to the industry [70].

In control applications, the selection of measurements entails finding a suitable set of CVs for use in the available control systems [76]. For the systematic selection of measurements for use as CVs, Skogestad [76] introduced the concept of self-optimizing control. Real-time optimizing control relies on the use of online measurements, a state estimator, and a process model to compute the optimal set-points for the CVs based on the maximization of the defined objective function (revenue) [76]. With real-time optimization (RTO), the truly optimal operation is achieved by incorporating all the information relating to the minimization of the objective function and the computation of new set-points online. In self-optimizing control, on the other hand, optimal linear combinations of measurements are selected as CVs, such that when held at constant set-points (without online re-optimization when disturbances occur) minimal average revenue loss is incurred [76]. For a factory with no online measurements of disturbances and frequent disturbance variations, the accurate implementation of RTO can be challenging. Hence self-optimizing control provides a simplified alternative, and its use can reduce or even eliminate the need for sugarcane factories to implement RTO.

2.3.4.1. Self-optimizing control

From a steady-state point of view optimal operation, for a given disturbance (d), the objective is to achieve optimal steady-state operation where the manipulated variables (u) are selected such that the scalar objective function (J) is minimized for any given d. The assumption of constant active constraints is often used in self-optimizing control. However, Cao [77] argues that some active constraints can change for some operating conditions and proposed a cascade control structure that seeks to satisfy both the self-optimizing requirements and the active constraints which vary with d and the measurement error n. By assuming that any optimally active constraints have been implemented, such that the remaining degrees of freedom u are those available for the optimization of the objective function, the optimization problem becomes (Equation 2-1):

$$\min_{u} J(u, d) \tag{2-1}$$

For any given disturbance value, solving Equation (2-1) will give $J_{opt}(d)$, $u_{opt}(d) = d$ and the output variables $y_{opt}(d)$. However, due to variations in the disturbances and the implementation error (measurements and set-point error), the controllers attempt to implement a constant set-point policy (or use non-optimal u) that will result in a loss, L. The loss, L in implementing self-optimizing control is, therefore, defined as the difference between the objective function value when a non-optimal input u is used and the truly optimal value of the objective function $J_{opt}(d)$ when RTO is done [76].

$$L = \left(J(u, d) - J_{opt}(d)\right) \tag{2-2}$$

The loss, L in self-optimizing control is because of:

i. **Set-point error due to unmeasured external disturbances,** $v(\mathbf{d})$ - With self-optimizing control, a closed-loop implementation is used, which attempts to implement a constant set-point policy [76]. Hence for a given disturbance, the set-point error is the difference between the constant set-point (c_s) and the optimal set-points as determined by RTO ($c_{opt}(d)$).

$$v(d) = c_s - c_{opt}(d) \tag{2-3}$$

ii. **Implementation error due to control and measurement error, n**- For a closed-loop system the assumption of zero steady-state control error is satisfied if an integral controller is used, so the only implementation error considered is due to the measurements [76]. Measurement errors result in a difference between the true value c of the CV and the constant set-point, c_s. Thus, the implementation error is:

$$n = c - c_s \tag{2-4}$$

Therefore, to select a combination of measurements (c) for use as constant CVs, the vector of the CVs can be expressed as c = H (y) [78], where H is a vector-valued function with respect to the process measurements (y). Any combination of measurements H may be freely chosen to facilitate self-optimizing [78]. The idea is that by carefully selecting the combination of the optimal measurements (c), the effect of disturbances will be compensated such that the need for RTO is reduced or even eliminated. The local second-order Taylor series expansion of the objective function in Equation (2-1) around the nominal operating point (u^*, d^*) is given as [76]:

$$J(u,d) = J(u^*,d^*) + [J_u \quad J_d]^T \begin{bmatrix} \Delta u \\ \Delta d \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \Delta u \\ \Delta d \end{bmatrix}^T \begin{bmatrix} J_{uu} & J_{ud} \\ J_{du} & J_{dd} \end{bmatrix} \begin{bmatrix} \Delta u \\ \Delta d \end{bmatrix} \tag{2-5}$$

Where, $J_u = \left(\frac{\partial J}{\partial u}\right)$, $J_d = \left(\frac{\partial J}{\partial d}\right)$, $J_{uu} = \left(\frac{\partial^2 J}{\partial^2 u}\right)$, $J_{ud} = \left(\frac{\partial^2 J}{\partial u \partial d}\right)$, $J_{dd} = \left(\frac{\partial^2 J}{\partial^2 d}\right)$, $\Delta u = u - u^*$ and $\Delta d = d - d^*$. A similar Taylor series expansion can be done for the loss function L defined in Equation 2-2 but unlike the expansion of cost function (Equation 2-5) which was done around the nominal point (u^*, d^*), the expansion of the loss function is done at the optimal point $(u_{opt}(d), d)$ for a given disturbance, as shown in Equation (2-6) [79]. The loss function is defined as $L = J(u,d) - J(u_{opt}(d), d)$, thus, the second-order accurate Taylor series expression for the loss function is [79]:

$$L(u,d) = \frac{1}{2}\left[u - u_{opt}(d)\right]^T J_{uu}\left[u - u_{opt}(d)\right] = \frac{1}{2} z^T z \tag{2-6}$$

Where

$$z \triangleq \sqrt{J_{uu}}\left[u - u_{opt}(d)\right]$$

The derivations for selecting linear combinations of CVs for facilitating self-optimizing control is considered in this study, thus

$$\Delta c = H \Delta y \tag{2-7}$$

From the process output variables, the number of variables that can be independently controlled (N_c) is equal to the number of the independently manipulated variables (N_u). However, often, the number of the output variables (N_y) is larger than the manipulated variables (N_u). Therefore, for attaining independent control the number of CVs selected must be equal to the number of degrees of freedom available for optimization. However, this gives rise to the problem of selecting the non-square matrix, H such that the transfer function from u to c is square [80]. The constant set-point policy seeks to adjust u such that $c_s = c + n$ where c has been affected by the disturbances and n is the implementation (measurement) error. In terms of the matrix H, freedom exists to choose different measurement combinations from y, and the measurement error for a selected combination is $n = Hn^y$ where n^y denotes all the available candidate measurements for selection [80]. Therefore, to define the loss variables, z in terms of d and n^y the locally linearized model of the process is used. The relationship between the inputs and the CVs is $c = f_c(u,d)$ and with the measurements it is $y = f_y(u,d)$. For small deviations of u and d around the nominal operating point, the linearized (local) models are:

$$\Delta y = G^{y} \triangle u + G_{d}^{y} \triangle d \tag{2-8}$$

$$\Delta c = G^{c} \triangle u + G_{d}^{c} \triangle d \tag{2-9}$$

Where, $G^{y} = \left(\frac{\partial f_c}{\partial u}\right)^{*T}$,$G_{d}^{y} = \left(\frac{\partial f_c}{\partial d}\right)^{*T}$, $G^{c} = \left(\frac{\partial f_c}{\partial u}\right)^{*T}$ and $G_{d}^{c} = \left(\frac{\partial f_c}{\partial d}\right)^{*T}$. The T stands for transpose. The non-linear functions $u_{opt}(d)$ and $y_{opt}(d)$ are also linearized to get:

$$\Delta u_{opt} = -J_{uu}\, J_{ud} \triangle d \tag{2-10}$$

$$\Delta y_{opt} = -\left(G^{y} J_{uu}{}^{-1}\, J_{ud} - G_{d}^{y}\right) \triangle d = F \triangle d \tag{2-11}$$

By introducing the optimal sensitivity matrix, F into Equation (2-7) it becomes:

$$\Delta c_{opt} = H \Delta y_{opt} = HF \triangle d \tag{2-12}$$

Therefore, from a linear view, the problem of selecting the best linear measurement combination (c) for use as constant CVs for self-optimizing control, entails finding the optimal combination matrix H.

Halvorsen et al. [81] proposed the choice of the optimum measurement combination matrix H, based on the exact non-linear formulation of the self-optimizing control problem. However, for high-dimensional and non-convex optimization problems, this formulation is tedious and can converge to a local optimum point [76]. Alstad et al. [78] derived an explicit expression for optimal H for the case where the objective is to minimize the loss, due to the combined effect of the disturbances and measurement errors on the controllers attempts to implement the constant set-point policy as:

$$H^{T} = \sqrt{J_{uu}}\, \left((G^{y})^{T} \left(\tilde{F}\tilde{F}^{T}\right)^{-1} G^{y}\right) (G^{y})^{T} \left(\tilde{F}\tilde{F}^{T}\right)^{-1} \tag{2-13}$$

Where,

$$\tilde{F} = [F W_{d} \;\; W_{n}^{y}] \tag{2-14}$$

The positive diagonal matrices W_{d} and W_{n}^{y} contain the magnitudes of the d and the measurement errors n associated with the candidate measurements y, respectively. The evaluation of the loss for a non-linear process is challenging [79]. Hence to quickly pre-screen the alternatives, local methods like the minimum singular value (MSV) rule [82] and exact local methods with minimization of the worst-case or average loss are used [5,13]. The MSV rule is used to select CVs that maximize the minimum singular value of the scaled gain matrix [82,83]. When compared to exact local methods, the MSV rules tend to perform poorly for ill-conditioned plants [83] and multivariable systems [79]. The worst-case loss tends to be conservative as the extreme values of the disturbances might be rarely experienced in actual factory operation [81].

Halvorsen et al. [79] derived the exact local expression for worst-case loss and average loss minimization as:

$$L_{wc} = \frac{1}{2}\sigma^2\, M \tag{2-15}$$

$$L_{ave} = \frac{1}{6(n_y + n_d)} \|[M]\|_F{}^2 \tag{2-16}$$

Where,

$\sigma(\cdot)$= Maximum singular value

$$M = [M_d \quad M_n] \tag{2-17}$$

$$M_d = \sqrt{J_{uu}}\,({J_{uu}}^{-1}J_{ud} - (HG^y)^{-1}HG_d^y)W_d \tag{2-18}$$

$$M_n = \sqrt{J_{uu}}\,(HG^y)^{-1}\, W_n^y \tag{2-19}$$

The loss due to disturbances and measurement errors is introduced through M_d and M_n. The notation $\|.\|_F$ represents the Frobenius norm of the matrix, M. The worst-case loss optimization problem depends on the minimization of the largest singular value of the matrix M while the average loss relies on the sum of the squares of all the singular values (inclusive of the largest singular value) of the matrix. Thus, the worst-case H matrix minimizes the largest singular value but does not necessarily minimize the contribution of the smaller singular values toward the average loss [81]. In this regard, it can be argued that the H matrix that minimizes the average loss should also minimize the worst-case loss [81]. Furthermore, the worst-case loss tends to be conservative as the extreme values of the disturbances might be rarely experienced in actual factory operation [81]. For these reasons, the average loss is deemed more realistic. The dependency of the loss variables $\mathrm{M_d}$ and $\mathrm{M_n}$ on the matrix, H is introduced through Equations (2-18) and (2-19).

2.3.4.2. Self-optimizing control example

Problem Statement: Given the following plant data and measurements of the four available candidate measurements, the goal is to determine the best measurement(s) to use as CVs when individual, combinations of two and all four measurements are considered [78].

Process variable classification: $\mathrm{N_u} = 1$, $\mathrm{N_d} = 1$ and $\mathrm{N_y} = 4$.

Objective function: $\mathrm{J(u,d) = (u-d)^2}$ with nominal disturbance, $d^* = 0$.

Uncertainty: $\mathrm{W_d} = 1$ and $\mathrm{W_n^y} = \mathbf{I}$ (thus each measurement is assumed to have an error of 1)

Candidate measurements: $y_1 = 0.1(\mathrm{u-d})$; $y_2 = 20\mathrm{u}$; $y_3 = 10\mathrm{u} - 5\mathrm{d}$ and $y_4 = \mathrm{u}$.

Solution: From the given objective function, $\mathrm{J_{opt}(d)} = 0$ and $\mathrm{u_{opt}(d) = d}$. The resultant second partial derivatives are $\mathrm{J_{uu}} = 2$ and $\mathrm{J_{ud}} = 2$. Using the available measurement equations, the transfer functions are $\mathrm{G^y} = [0.1\ 20\ 10\ 1]^\mathrm{T}$ and $\mathrm{G_d^y} = [-0.1\quad 0\ -5\quad 0]^\mathrm{T}$. From Equation (2-11) the optimal measurement sensitivity to the disturbances is, $\mathrm{F} = [0\quad 20\ 5\quad 1]^\mathrm{T}$. For the single measurements, the worst-case and average losses attained by using Equation (2-15) and (2-16) are:

$L_{wc1} = 100$; $\mathrm{L_{wc2}} = 1.0025$; $L_{wc3} = 0.26$ and $L_{wc4} = 2$

$L_{ave1} = 16.67$; $L_{ave2} = 0.167$; $L_{ave3} = 0.043$ and $L_{ave4} = 0.33$

The best single measurement is shown to be y_3 while the use of measurement y_1 as a CV result in the largest worst-case loss and an average loss of 100 and 16.67, respectively. The worst-case loss values are higher than the average loss because the worst-case loss depends on the minimization of the maximum singular value of the matrix M. Choosing two measurements out of 4 candidate measurements, results in six $\left(\frac{4!}{2!\times(4-2)!}\right)$ candidate measurement combinations. Table 2-7 provides the worst-case and average loss when measurement combinations of two and all four measurements are considered. The measurement combination with variables y_2 and y_3 is found to be the best combination with a worst-case loss and average loss of 0.0406 and 0.0045, respectively. The use of Equation (2-13) gives a lower sensitivity to measurement errors [78]. Hence, although the best combination has a higher loss contribution from the measurement errors as compared to combinations like y_2 and y_4, it is relatively less sensitive to the uncertainty in the disturbances ($\mathrm{M_d} = -0.0606$) as compared to other combinations.

Table 2-7: Loss evaluation for measurement combinations in the presence of disturbances and measurement errors

Measurements		**Optimal H**		**Mn**	**Md**	**G**	**Loss**	
							Worst-case	Average
All 4		[0.021 -0.232 0.973 -0.012]		0.2783	-0.0606	5.082	0.0405	0.0027
y_2	y_3	-0.232	0.973	0.2783	-0.0606	5.081	0.0406	0.0045
y_3	y_4	0.530	-0.848	0.3177	-0.5724	4.452	0.2143	0.0238
y_1	y_3	0.252	0.968	0.1457	-0.7053	9.703	0.2593	0.0288
y_1	y_2	0.895	0.446	0.1569	-1.400	9.016	0.9925	0.1103
y_2	y_4	0.999	0.050	0.0706	-1.41421	20.025	1.0025	0.1114
y_1	y_4	0.196	0.981	1.4139	-1.3865	1.0002	1.9608	0.2179

For the selection of 2 measurement combinations, there are only 6 different combinations to evaluate, hence an exhaustive search could be done. However, as the process dimensions increase, such an exhaustive search is not possible, and an efficient method (exploration and computation time) is thus required to find the best CV measurements for self-optimizing control. Hence methods like the branch and bound [18], mixed-integer linear programming techniques [86], and genetic algorithms (GAs) [87] are often employed for selecting measurements as CVs for self-optimizing control. There are no known studies that have used the concept of self-optimizing control for optimal sensor placement, the concept is often restricted to the selection of CVs based on fixed measurement specification.

2.3.5. Standard operating procedures

Standard operating procedures (SOPs) are instructions set up by a factory to assist plant personnel to operate their process units in an effective manner [27]. Due to the interaction that exists between process units in a sugarcane mill, such SOPs should explicitly detail the operation of each process unit in conjunction with its impact on the operation of the other process units. Therefore, to understand some of the operational practices and targets, questionnaires were drafted for this study and distributed in South African and Australian sugarcane mills. The questionnaire templates are provided in Appendix A. Based on the review of the questionnaire responses it was observed that some variables often stated in research studies to have an impact on factory operation are not measured. Also, in some instances, there were variations in the target values stated by plant personnel operating the same unit at different production shifts. For example, in the boiler unit, there were differences of approximately 10℃ in target steam temperatures.

While a detailed investigation would be required to test the significance of such discrepancies on the energy consumption outlook of a factory, results suggest there could be a significant benefit in establishing SOPs across all shifts. The SOPs must adequately indicate the production and energy implication of variations in the target values of the CVs. Based on these deductions, there is a need for the installment of measuring equipment and the review of the currently available SOPs to ensure that excess energy consumption monitoring and correction imperatives are included. Such SOPs must seek to achieve energy conservation awareness and uniformity of performance while reducing miscommunication amongst plant personnel and unconformity to the operational regulations.

2.4. Conclusions

Based on the review of the pertinent literature in Section 2.3, Table 2-8 provides a list of the identified research gaps relative to the needs of the sugarcane industry to improve their energy efficiency, thereby resulting in additional revenue from surplus bagasse.

Table 2-8: Identified research gaps in addressing the sugarcane industry needs to improve their energy efficiency and profitability

Sugarcane Industry Needs	Research/Literature Gap Description
1. Energy indicators that are integrated with variables that influence energy consumption or that can be controlled to correct energy inefficiencies.	The available energy indicators in literature are often defined as a ratio of the useful energy input (or output) to the useful output (or input). Although these energy indicators are useful for energy reporting and benchmarking on their own they provide inadequate information on the CVs whose precise monitoring and control are required for improved energy efficiency while ensuring the process unit interactions are addressed for the generation of desired control outcomes.
2. Comprehensive knowledge of the effect of the unavoidable external disturbances on the steady-state energy usage of the factory. This is essential for formulating possible corrective actions.	Sensitivity analysis is often used which considers only a subset of the values of the process disturbances and market prices; hence no information about their stochastic properties is provided and relevant information can be missed.
3. Optimal control and design solutions that are robust and resilient to variations in the process disturbances and market prices.	The optimization studies for optimal control often use the averaged values of the external disturbances. Hence the optimal solutions will only be optimal for the considered disturbance values and will leave the factory vulnerable to the day-to-day variations of these external disturbances.
4. More measuring instruments and precise measurements that the factory can justifiably invest in to enable effective process monitoring and control.	Some studies qualitatively discuss possible instrumentation solutions for sugarcane mills based on process knowledge and intuition. But these studies lack scientific support for application in the profitable design of a plant-wide sensor network. No known studies show the economic value of precise sensors in a sugar mill.
5. Scientifically grounded and unbiased approach for balancing energy usage reduction and sugar production improvement when operating under the random variations of the external variables.	Inadequate studies that translate energy usage to monetary terms to allow for easy comparison with the expected revenue from the produced sugar. Also, when such studies are done the inherent randomness of the external disturbances is ignored.

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Chapter 3

3. Study Rationale, Objectives, and Methods

3.1. Study rationale and objectives

The shift in the economic and operational drivers of sugarcane mills has prompted a need for the industry to address the causes of energy and economic inefficiencies (Figure 2-11) to improve the factory energy efficiency and profitability through additional revenue from surplus bagasse. However, from Section 2, research gaps were identified relative to the needs of the sugarcane industry to address the cause of energy and economic inefficiencies. Considering the available research gaps and the sugarcane industry needs, the overall aim of this study is to develop an improved energy management system for sugarcane mills through enhanced process monitoring and plant-wide control. The primary objectives set out to achieve the study aim are to:

1. Determine the CVs whose steady-state deviation leads to excess energy consumption, through energy indicator definition, sensitivity, and statistical analysis
2. Evaluate the stochastic risks associated with the random variations in the process disturbances and market prices
3. Investigate the potential benefits of implementing set-point optimizing control when process disturbances and market price variation occur.
4. Find an economically optimal sensor placement for a typical sugarcane mill based on the self-optimizing control concept and genetic algorithms.

3.2. Study methods

3.2.1. Model selection

A model of a typical sugarcane mill is required for accomplishing the study objectives. The selected process model must, therefore, apply to the present study objectives. Accurate process simulation is required for the prediction of the energy consumption distribution in the sugarcane mill. The use of simulation models is a quick and efficient way to evaluate changes in energy usage patterns in different operational scenarios. The comparison of two simulation software, Sugars® [1,2] and the MATLAB sugar mill model [3] was done to choose only one of these two well-established simulation models. The Sugars® software package is a process flow-sheeting program that is specific to the sugar industries and includes a process economic analysis facility [4]. The Sugars® software provides wide flexibility of configurations, such that equipment for a particular model block may be arranged in any technically feasible manner, without interfering with the execution of the program [1]. Owing to its flexibility, the Sugars® model can calculate material, energy, and color balances of most sugar processes regardless of the processing technique or equipment used [4]. The Sugars® model is reported to have been used to develop mass, energy, and color balances for two sugarcane mills in South Africa with good prediction results [4].

Considering the high prediction accuracy of the Sugars® model, the mathematical correctness of the MATLAB sugarcane mill model was successfully verified against the simulation results from Sugars® for the same input data [3]. Negligible discrepancies were observed due to the differences in the modeling of the diffuser and vacuum filter [3]. In the MATLAB model, the diffuser is simply configured as a single well-mixed tank while in Sugars® a more intuitive approach was used to represent the diffuser as a compartmental unit consisting of interacting tanks. Also, the mud vacuum filter in the MATLAB model is a single system and in Sugars® this is modeled as two-compartmental systems. The boiling point elevation formula developed by Kadlec et al. [5] in 1978 is used in Sugars® while in the MATLAB model the recently developed formula by Saska [6] is used. The results of the MATLAB model verification and comparison against Sugars® are provided in [3,7]. Also, 194 variables from seven South African sugarcane mills that have a similar configuration (mud filtration and the three-boiling partial remelt scheme) to that represented in the MATLAB model were used for validating the model [3]. To generate a set of data that represents a generic South African mill, the validation data were averaged across all seven sugarcane mills. The model showed good agreement with observed factory data [3]. The MATLAB sugar mill model was verified against the commercial Sugars® model and validated against seven factories with a similar configuration, the results attained from its use can thus be trusted. The process model is for a typical sugarcane factory that processes 250 tonnes of sugarcane per hour and produces 30 tonnes of raw sugar per hour at steady-state conditions. At these steady-state conditions, the available surplus bagasse is 31.06 tonnes/hr.

MATLAB has several tools for optimization, distribution fitting, and Monte Carlo analysis. For these reasons, despite the equivalent predictive abilities of both models, the MATLAB sugarcane mill model is selected for use in fulfilling the present study objectives. The boiler unit was shown in Section 2 to contribute to 29% of the bagasse energy wastages through the flue gas heat losses. However, the boiler section in the MATLAB model is simulated as a simple heat exchanger unit. This obscures the evaluation into possible control or waste recovery strategies to implement to reduce the flue gas-related heat losses. Hence, the present study investigations involving the calculation of the boiler energy indicator are based on the Aspen Plus® boiler configuration model for a generic sugarcane mill (processes 250 tonnes of sugarcane per hour) developed by Dogbe et al. [8].

3.2.2. Objective 1 methods

Objective 1 entails the identification of CVs with an influential effect on energy efficiency and hence whose precise monitoring and control are necessary. The methodology used for this objective is provided in Figure 3-1.

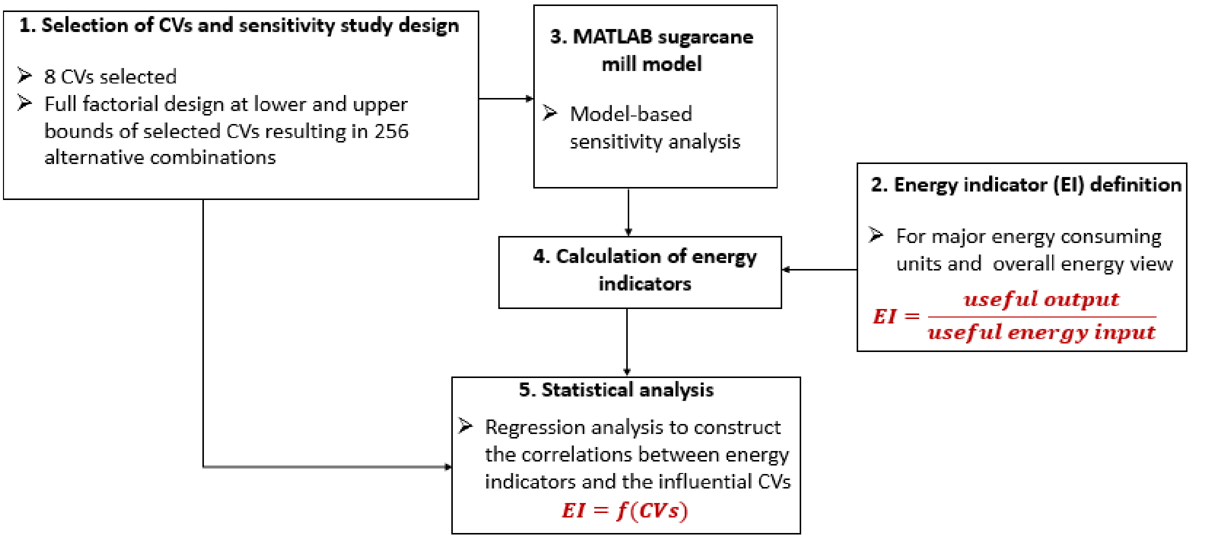

Figure 3-1: Methods outline for objective 1

From Section 2, the evaporation and crystallization units were observed to be the major energy-consuming units that use 19% and 17% of the available bagasse energy, respectively. Owing to the high latent heat of vaporization of water most of the energy used in a sugar mill is for the evaporation of water. Significant amounts of water are evaporated in both the evaporation and the crystallization unit. For these reasons, their energy indicators were defined as a ratio of the energy used to the quantity of water evaporated (kWh/kg of water evaporated). To allow for an overall energy consumption perspective of typical sugarcane mills, two additional energy indicators were defined as HP steam heat used per tonne of cane and the HP steam heat required per tonne of sugar produced. Eight variables considered to have an impact on the energy demands were selected from different process units. The full factorial design is employed for sensitivity studies. In full factorial designs, each model update considers all possible combinations of the variables being investigated [9]. For example, for a "k" number of variables, each having two values specified, the number of observations $= 2^k$. Factorial designs allow the effect of a variable on the defined energy indicators to be evaluated and estimated at several values of the other variables, yielding conclusions that are valid over a wide range.

The CVs considered for the sugar production section are imbibition water flow, the dissolved solids content of syrup as well as the dry substance concentration and temperatures of the A, B, and C massecuite streams. Considering that the selected variables are from different process units, the use of a full factorial will enable the identification of significant process unit interactions from an energy view. In the present study, for each variable its lower and upper allowable values are used in the sensitivity design, thereby yielding 256 combinations for use in the model update. The typical lower and upper operating constraints for these variables were obtained through a literature review [3,10] and the evaluation of the questionnaires submitted to the sugarcane factories (Appendix A1). Statistical analysis is employed for analyzing the observed energy indicator responses from the sensitivity studies. To understand, establish, and quantify the relationship between the statistically significant variables and each defined energy indicator, a linear regression model is fitted to the observed energy indicator data means. A similar strategy as that shown in Figure 3-1 for the sugar production units was used for the boiler unit based on the Aspen Plus® of a typical cogeneration system in a 250 tonnes/hr sugarcane factory. Two energy indicators were defined for the boiler unit and an economic indicator for evaluating the cost of generating HP steam. The Aspen Plus® model only allows for the variation of one variable at a time. Therefore, unlike the depiction in Figure 3-1, 5 CVs are selected for the boiler study, and each selected CV is independently varied for evaluation of its effect on the defined energy and economic indicators evaluated. For the boiler study, 5 CVs were selected for analysis namely the bagasse moisture content, the temperature of condensates returned as boiler feedwater, the percentage of cold water used to supplement the feedwater, flue gas temperature, and oxygen concentration.

3.2.3. Objective 2 methods

Objective 2 is on the evaluation of the stochastic risks associated with the random variations in the external disturbances and market prices. Figure 3-2 provides an outline of the methods used for accomplishing objective 2. The simulated disturbances in the sugarcane mill process model are sugarcane flow, fiber, sucrose, and DS content as well as air temperature and humidity. The financial model is the factory net revenue defined as the difference between the product's revenue (sugar, surplus bagasse, and molasses) and the cost of the raw materials (sugarcane and lime).

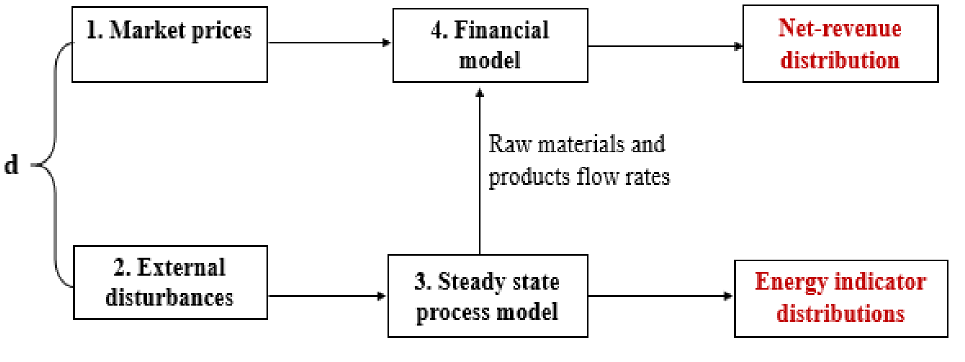

Figure 3-2: Objective 2 methods outline

The annual review reports of the 2010 to 2018 sugar milling season in Southern Africa were used to obtain historical data for the external disturbances and the relevant sources were used to obtain the market prices for the same time frame [10–17]. The collected data was used to estimate the probability distributions of the considered disturbances and market prices. The process disturbances and market prices are inherently random; therefore, Monte Carlo is used to randomly choose and simulate their input values based on the estimated distributions. Since the values of the input variables in both models are selected using the probability distributions that they follow in real-life, the attained output distributions of the energy indicators and net-revenue will reflect their expected frequency of occurrence in practice. To quantify the operating profitability of a sugarcane factory, the scalar objective function is defined as the net-revenue (J) which considers the product's revenue and the raw materials costs while the energy indicators are defined through the fulfillment of objective 1 are used for quantifying energy usage.

3.2.4. Objective 3 methods

Objective 3 seeks to investigate the potential benefits of using set-point optimizing control to mitigate the steady-state energy and economic effects (observed in objective 2), due to the random variations in external process disturbances and market prices. The methodology used for objective 3 is outlined in Figure 3-3.

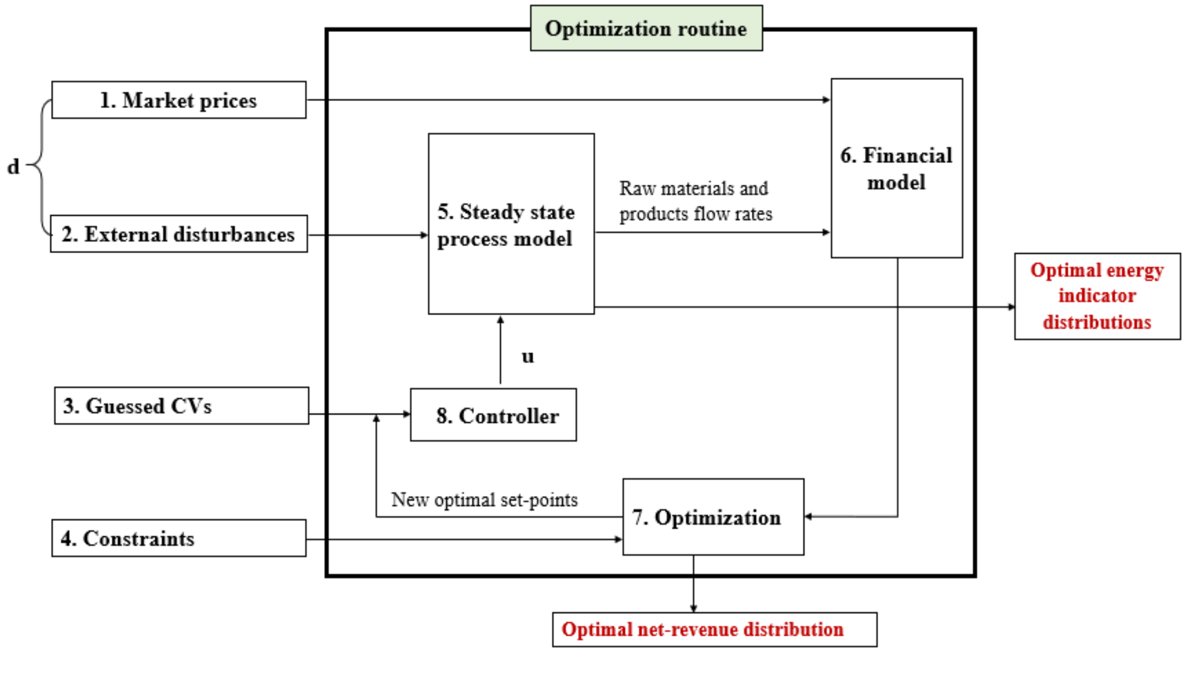

Figure 3-3: Objective 3 methods outline

Fourteen CVs including those identified from the fulfillment of objective 1 are considered for use as decision variables for set-point optimization. The selected CVs are provided in Table 6-1. Factory constraints are also considered in the optimizer to ensure the results are within the feasible operating region of the sugarcane mill. Therefore, for given values of the disturbances (d), the set-point optimization strategy in the present study seeks to maximize the factory net-revenue (J) by finding new optimal set-points for the 14 CVs. To evaluate the benefits of implementing set-point optimization the output distributions (net-revenue (J) and energy indicators) from objective 2 when no optimization is done are compared to the distributions of the optimal energy indicators and net-revenue, Jopt when set-point optimization (Figure 3-3).

The global optimization toolbox in MATLAB includes solvers like the genetic algorithm, surrogate, and pattern search [18]. Each solver possesses different search characteristics; hence it is considered essential to select a solver best tailored for the defined optimization problem. Surrogate optimization is useful for computationally expensive, black box, and global optimization problems with bound constraints [18]. Both pattern search and GAs can handle optimization problems involving linear, non-linear, and bounds constraints [18]. Among these three optimization solvers, GAs is the only one that can handle integer constraints. For the present study, the goal is to update the optimizer 5000 times according to the disturbance values, therefore computational speed is important. While the surrogate algorithm is slower than gradient-based solvers it is faster compared to pattern search and GA [18]. For these reasons, the surrogate algorithm is selected for use in the set-point optimizer. The use of the surrogate optimization method does not imply that a surrogate model of the process is optimized. Rather, surrogate optimization refers to a global optimization routine that evaluates the rigorous steady-state plant model at quasi-random points in the input space, then uses this information to construct a surrogate model using basis function approximation. The surrogate model is then used to speed-up intermediate calculations while reserving carefully selected points for the optimization of the rigorous plant.

Furthermore, surrogate optimization was selected as a global optimization algorithm is required to avoid local minima. The sugarcane mill model used in this study is complex, therefore, the analytical or numerically reliable derivatives are not available for use in set-point optimization. Moreover, for relatively high dimensional optimization problems such as those considered in this study, gradients obtained directly from using finite differences are often computationally expensive due to several required model evaluations and can be prone to numerical noise. For such instances, where the evaluation of the cost function or the gradient is time-consuming or too complex, the surrogate-based optimization approach is often recommended as an efficient adaptive method for reflecting the information of the underlying black-box model [18]. A detailed description of the MATLAB code and considerations made in the implementation of the set-point optimization strategy based on a surrogate optimization is provided in Appendix A2.

3.2.5. Objective 4 methods

To select the optimal linear combination of CVs and their respective optimal sensor placement for facilitating self-optimizing control in sugarcane mills, the GAs is used as they can handle integer optimization problems for large systems. The GAs is a population-based searching algorithm that uses the evolution idea of survival of fittest to search [24,25]. A population of chromosomes is created randomly to start the search, for the present study the brute force method was used to create the initial population. Each chromosome represents a sensor combination, and the component of a chromosome (gene) denotes the location and non-location of a sensor using the integers 1 and 0, respectively [4,5]. For example, if the chromosome is 0110, this means that the selected sensors (and CVs) are in positions 2 and 3. If a variable can be measured with more than one sensor, it should be repeated in the vector y, which represents the measurable process output variables. From the allocated sensor locations in the sensor combination (chromosome), the corresponding linear combination of CVs (c), the sensor errors (W_n^c), G^c and G_d^c are applied for self-optimizing control together with W_d and the Hessian matrices, J_{uu} and J_{ud}. At this stage, the self-optimizing control capabilities of the selected sensor placement are tested by computing the H matrix and the average loss, L_{ave} due to the disturbances effect on the linear combination of CVs (c) and the impact of the sensor errors. Denoting the total cost of purchasing the selected sensor combinations as J_{sc}. The optimal sensor placement (C^*) is, therefore, finally determined using J_{sc} and L_{ave} by combining them in a common weighted criterion $J_T = (1-k)J_{sc} + kL_{ave})$, where k = 0.5. Therefore, the optimal sensor placement is formulated as:

$$C^* = \min_{C \in y^{all}} (J_{sc} + L_{ave}) \qquad (3\text{-}1)$$

If the optimal solution cannot be obtained analytically an iterative procedure is used and a new sensor combination (chromosome) is selected. Reproduction, crossover, and mutation probability are important genetic operators used to produce a new chromosome (offspring) [24,25]. A detailed description of the MATLAB code and considerations made in the implementation of the optimal sensor placement strategy based on GAs is provided in Appendix A3. The sugarcane mill model used in the present study was developed for design purposes hence in some instances output process variables were considered as input variables and the manipulated variables as the output variables. To overcome this shortcoming a systematic approach provided in Appendix A4 was used for the numerical evaluation of the partial derivatives in the present study.

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Chapter 4

4. Disturbance Modeling Through Steady-State Value Deviations: The Determination of Suitable Energy Indicators and Parameters for Energy Consumption Monitoring in A Typical Sugar Mill

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The objective of the dissertation in this chapter and the summary of findings

In this chapter, objective 1 (see Section 3) is addressed for the production units based on the MATLAB sugarcane mill model. Objective 1 involves the evaluation of the relationships between process variables and energy usage through energy indicator definition, sensitivity, and statistical analysis. Energy indicators were defined for the evaporation and crystallization unit as they are the major energy-consuming units responsible for 36 % of the bagasse energy usage. Most of the energy in these process units is used for water evaporation, therefore their energy indicators were defined as the energy required per kg of water evaporated. From an overall energy perspective of the factory, two energy indicators were defined for HP steam usage as $\mathrm{kWh/tonne\ sugarcane}$ and $\mathrm{kWh/tonne\ sugar}$. Sensitivity and statistical analysis were used to evaluate and identify the CVs whose steady-state deviations result in excess energy usage in the evaporator, crystallization, and overall factory. Eight CVs were selected for use in the analysis namely; the ratio of imbibition water added to the sugarcane fiber content (IW), syrup DS content, the A, B, and C massecuite DS contents, and the operating pressures in all three pan stages.

The steady-state deviations in the syrup DS content, A-massecuite DS content, and IW were observed to have a cumulative effect of 82% on the energy used per kg of water evaporated in the evaporator unit. Therefore, for improved operation of the evaporator unit, the optimal control of syrup DS content, IW addition, and A-massecuite DS content in the evaporator, extraction, and crystallization unit, respectively is required. By using a full factorial design comprising of CVs from different process units, this chapter was further able to successfully capture the significant process unit interactions from an energy outlook. The steady-state deviations in A and B massecuite DS content and their respective pans operating pressures were observed to contribute 28, 12, 31, and 14% of the effect in the energy used in the crystallization unit to evaporate a kg of water. Overall, this chapter was able to identify important CVs for improved energy efficiencies in the sugarcane mill through enhanced process monitoring and control. The CVs observed in this chapter to have a major effect on the energy usage are considered as decision variables for set-point optimization (Chapter 6) and optimal sensor placement based on the self-optimizing control concept (Chapter 7). The word parameters in the published paper have been changed to variables for consistency with the rest of the dissertation chapter.

Declaration by the candidate

With regards to Chapter 4, the nature and scope of my contribution were as follows:

Nature of contribution	The extent of contribution (%)
Project and scope definition, analysis of data, interpretation of results, and writing of the chapter	80

The following co-authors have contributed to Chapter 4.

Name	e-mail address	Nature of contribution	Extent of contribution (%)
J.F. Görgens	jgorgens@sun.ac.za	General discussions and provided writing assistance through the review of the chapter.	8
M.A. Mandegari	mandegari@sun.ac.za	Assisted in the development of the chapter scope. Provided continuous review and proofreading of the chapter.	12

Signature of candidate:

Date: March 2021

Declaration by co-authors:

The undersigned hereby confirm that

1. the declaration above accurately reflects the nature and extent of the contributions of the candidate and the co-authors to Chapter 4
2. no other authors contributed to Chapter 4 besides those specified above, and
3. potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 4 of this dissertation.

Signature	**Institutional affiliation**	**Date**
	Stellenbosch University	
	Stellenbosch University	
	Stellenbosch University	

Disturbance modeling through steady-state value deviations: The determination of suitable energy indicators and parameters for energy consumption monitoring in a typical sugar mill

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Abstract

The growing emphasis on alternative revenue streams from the conversion of sugarcane bagasse into energy co-products has prompted a desire by the sugar factories to achieve higher levels of energy efficiency. This study presents a comprehensive overview of the variables whose steady-state deviation leads to excess energy use in sugar mills. The effect of eight operating variables on the defined energy indicators was investigated, using a MATLAB simulation of a 250-tonne per hour sugar mill. The captured energy trends were used to develop energy prediction models based on the variables whose steady-state offsets resulted in excess energy use. High prediction accuracies of over 95% were obtained when the developed energy prediction models were validated for seasonal cane quality and evaporator heat transfer coefficient variations. Increased A-massecuite recycling had a more pronounced effect on the energy used per kilogram of water in the evaporator unit as compared to the crystallization unit. Of the eight variables, elevated imbibition water use and A-massecuite recycling had a cumulative percentage effect of 79% on the overall steam used per tonne of cane and sugar produced. Hence increasing the syrup concentration, decreasing imbibition water use and massecuite recycling are preferred operational strategies for improved energy-efficiency in a sugar mill. Overall, this study strengthens the existing literature by illustrating an approach for developing suitable energy indicators for excess energy use monitoring in sugarcane mills.

Keywords: Energy indicator; Disturbance; Sugar mill; Energy benchmarking; Statistical analysis; Energy monitoring

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4.1. Introduction

Sugar cane is one of the most important agricultural products in the world and is mostly produced in developing countries such as Brazil, China, India, and South Africa [1]. The increasing energy demands, reducing fossil fuel stocks and global warming concerns have made bagasse, a fibrous residue from sugarcane processing, a vital resource for electricity [2], biochemicals [3], and biofuels [4] production. The growing emphasis on alternative revenue streams from the production of bio-based products has prompted a desire by the sugarcane factories to achieve higher levels of energy efficiency, thereby resulting in surplus bagasse. The evaluation of energy systems is usually done by applying the first or second law of thermodynamics [5]. Previous studies have applied the second law of thermodynamics to evaluate the efficiency with which available energy (exergy) is consumed in biorefineries [6], beet sugar [7], and sugarcane [8] factories. This paper will use the first law of thermodynamics to provide a comprehensive and quantitative analysis of the energy flows in the sugar production processes.

One of the impediments to good energy management practices in sugarcane mills is the lack of energy consumption monitoring which will allow for early detection of areas of energy peaks and wastage areas, mostly as a result of operator actions and/or process transients [9]. The sugar mill is comprised of many connected processes; consequently, the operation of a particular unit and its output, if unstable can adversely influence the performance and energy efficiency of other process units. Therefore, a well-structured energy monitoring system is required to enable early detection and correction of excess energy consumption resulting from operational variations. For this to be possible, suitable energy indicators must be developed to evaluate the process units and overall factory energy performance of sugarcane mills.

The percentage of the steam used to the cane throughput (steam % cane) is the commonly used plant-level energy indicator for overall energy consumption in sugarcane mills [10]. However, the fiber content of cane influences the available bagasse energy content and the amount of steam produced per tonne of cane crushed. This factory level index is more useful for internal benchmarking but lacks adequacy for external energy benchmarking as the cane quality differs from the factory and crushing season [10]. Kinoshita [11] recommends an alternative factory level index as the Net Power Generation/Cane Fiber Rate (kWh/tonne of fiber) for evaluating energy generation as a function of the cane fiber content. This index provides means to benchmark different sugar mills despite the cane quality variations, but it does not consider possible variations in the raw sugar quality. Although previous studies have focused on the definition of overall factory level energy indicators, these indices provide little information on the contribution of the process unit activities and their variation to the overall factory energy balance.

ENERGY STAR a US Environmental Protection Agency program uses a statistically developed energy performance indicator to identify the relationship between energy usage and production activities [13]. Boyd et al. [13] further describe how the energy performance indicator can be utilized as an energy benchmarking tool for comparable manufacturing industries. Similar statistical analysis methods have been used to establish energy prediction models based on the variables which influence energy consumption for residential buildings [14], injection molding [15], and polymer extrusion [16] processes. While the common approach has been to link energy usage to the production output, new approaches for correlating energy usage to the driving factors or process economics have gained attention [17].

Research gaps were identified in the quantitative breakdown of the overall factory energy consumption based on process unit activities and the establishment of energy monitoring systems in sugarcane mills. Therefore, this study aims to illustrate the methods which can be used for developing energy indicators for excess energy consumption monitoring in sugarcane mills. The methods are illustrated based on a MATLAB simulation of a typical 250-tonnes cane/hour factory. A series of energy indicators are defined to provide a comprehensive and quantitative view of the changes in the energy demands of a sugarcane factory with operational variations from steady-state conditions.

4.2. Research methodology

4.2.1. Raw sugar mill process description

Figure 4-1 shows the operational units and main flow streams in a typical sugarcane mill. The sugar mill configuration is split into two sections namely the raw sugar production units and the utility system. The production of raw sugar consists of juice extraction, clarification, evaporation, crystallization, and drying processes. The utility section consists of the cogeneration system and the cooling system which provide the steam, electricity, and cooling water requirements of the sugar processing units.

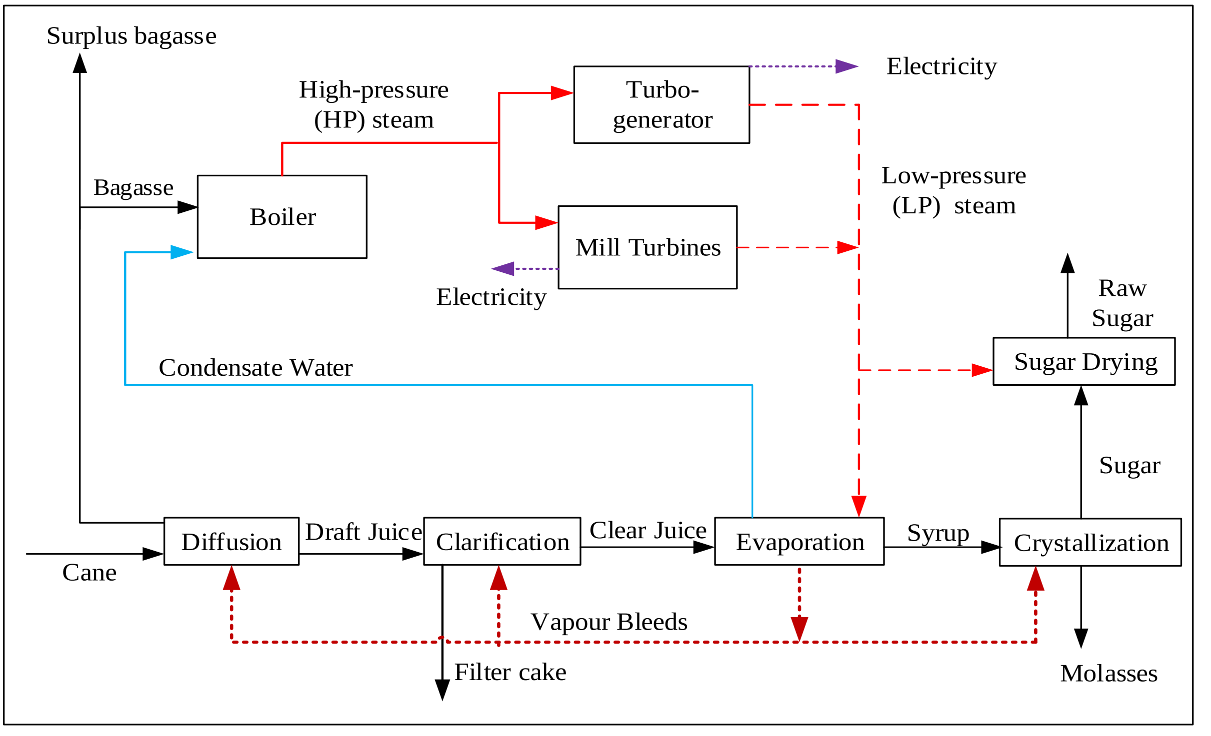

Figure 4-1: Typical Raw Sugar Mill Process in sugar mills

4.2.1.1. Extraction plant

The starting point in the production of raw sugar is the cell rupture of sugarcane using knives and shredders to facilitate sucrose extraction in the milling tandem or diffuser. Imbibition water is added in both methods to maximize the extraction of sucrose-containing juice. The installed power for milling tandems (excluding cane preparation) is approximately 90-100 kWh/tonne cane fiber as compared to 45-50 kWh/tonne cane fiber for a diffuser system with a dewatering mill [18]. Therefore, the diffuser with a dewatering mill is the preferred method for sucrose extraction in most sugar factories [18] and this is the configuration used in the simulated MATLAB sugar mill. After sucrose extraction in the diffuser, the fiber residue, bagasse, is compressed in the dewatering mills.

4.2.1.2. Clarification plant

The juice extracted from the diffuser, most commonly termed draft juice, sludge from the syrup filter, and the juice recovered from the vacuum filter are mixed before being heated to above the boiling point to permit for effective flashing and efficient settling in the clarifier [18]. Flashing removes the air bubbles from the suspended particles, which if not removed would otherwise prevent the particles of bagasse from settling in the clarifier. The impurities from the draft juice are removed in the clarifier, to produce clear juice. The resultant mud is either recycled back to the diffuser or fed to a rotary vacuum filter.

4.2.1.3. Evaporation unit

Preceding the multiple-effect evaporators is the clear juice heater which uses low-pressure exhaust steam to raise the temperature of the clear juice to allow flashing to occur upon entry to the first effect. The clear juice is concentrated in the multiple effect evaporators from approximately 13 Brix to 65-68 Brix [18]. Brix (°Bx) is a measure of dissolved solids in a sugar juice, liquor, or syrup, expressed as grams of solids per 100 grams of a solution [18]. Multiple effect evaporation consists of the re-use of latent heat for successive evaporations after the first effect, which uses the low-pressure exhausted steam from the turbogenerator and the mill turbines. The vapor requirements of the extraction, clarification, and crystallization unit are sustained using the vapor extracted from the evaporator unit.

4.2.1.4. Crystallization and sugar drying unit

The syrup is further concentrated to saturation under vacuum in batch or continuous pans to achieve sucrose crystallization. Process vessels in the sugar industry that operate under vacuum do so using a condenser system, which comprises a condenser and vacuum pump. Crystallization is enhanced by the addition of seed grains or magma to the massecuite, which is a mixture of mother liquor (molasses) and sugar crystals. The massecuite is cooled and mixed to ensure further crystallization in the cooling crystalliser. This massecuite is separated in the centrifuges to sugar and molasses. The crystallization process is often conducted in stages of two or three to ensure maximum sucrose recovery [18]. The sugar from A-pan is sent for drying while the molasses is recycled to the successive pan stages. The sugar from the subsequent pan stages is used to produce magma and the re-melt mixture which are fed to the A-pan.

4.2.1.5. Utility section

The fiber residue, bagasse, from the dewatering mills in the extraction plant, is incinerated in the boiler unit to generate steam. The high-pressure steam generated from the boiler is used to generate power in the turbo-generators and the mill turbines while the low-pressure steam is used as a heating medium for the clear juice pre-heater, first evaporator effect, and the sugar dryer. The term high-pressure (HP) steam is used in this paper to distinguish the steam from the boiler at 31 bar to the exhausted steam at 2 bar from the mill turbines and turbo-alternator which is of lower pressure in comparison. The term low-pressure (LP) steam is used for the exhausted steam exiting the turbines. The cooling tower provides the water used in the barometric condenser and auxiliaries.

4.2.2. Overview of raw sugar mill process model

The present study is based on a MATLAB simulation of the mass and energy balance of a generic sugarcane mill with a 250-tonne per hour cane throughput and steam consumption of 400 kilograms per tonne of cane [19]. The MATLAB model depicts a sugar mill configuration consisting of a diffuser with a dewatering mill, clarification with mud filtration, five-effect evaporation, a three-stage crystallization scheme with a partial re-melt, and sugar drying. Steam turbines are used as prime movers for the shredders, cane knives, and boiler feedwater pumps. The utility section is made up of the boiler, turbo-alternator, and cooling tower. The model was validated based on over 50 performance variables from seven South African sugarcane mills with a similar configuration [19]. The original data from the seven sugar mills were averaged to generate an optimal data set for the MATLAB sugarcane mill model, thereby providing a generic model of a sugar mill with this design configuration [19]. The calculation results from the MATLAB sugar mill model compared favorably with those obtained from the commercial Sugars® simulation model for the same set of input data [19].

The MATLAB sugar mill model only considers the thermodynamic energy demands of the process units with phase, composition, temperature, and pressure changes. Therefore, the auxiliary energy uses like pan steaming are not represented. The model was also developed for design purposes, hence modifications were made to enable a representation of the sugarcane mill operations. The model is based on steady-state operating conditions, therefore, to allow for investigation of the energy trends in a sugarcane factory during steady-state operational deviations, the disturbances must be modeled into the model.

4.2.2.1 Energy supply perspectives in sugar mills

The unit operations used in the production of raw sugar consume energy in the form of power for crushing, pumping, evaporation, centrifugation, and drying. Sugar mills typically require 325–550 kg of steam per tonne of sugarcane, but, by using energy-efficient practices and state of the art technology, the steam requirements can be as low as 280–300 kg-steam/tonne of sugarcane [20]. Figure 4-2 illustrates the energy supply network of a generic sugarcane mill as depicted in the MATLAB model and Table 4-1 provides an additional list of the base conditions of the simulated sugar mill.

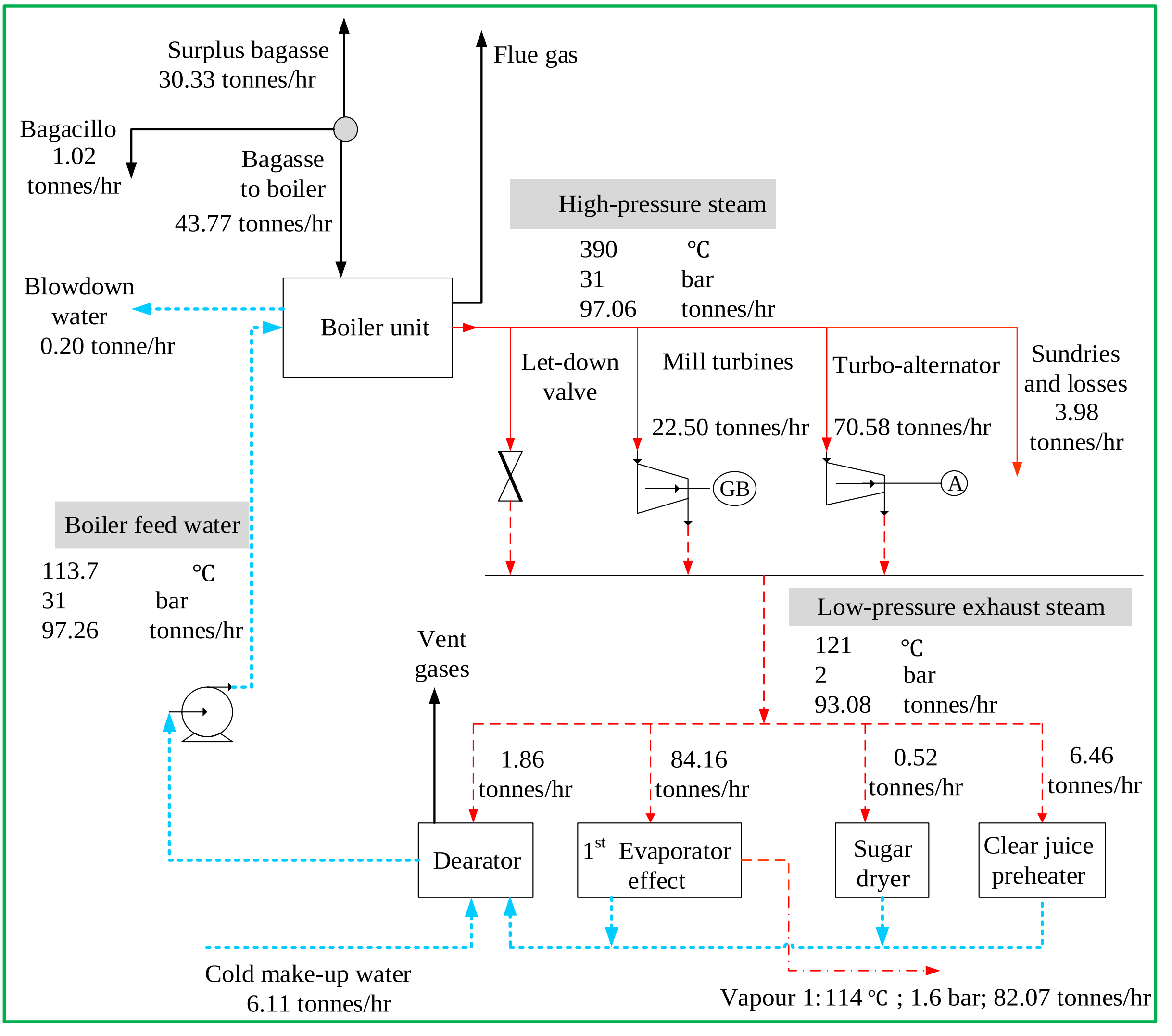

Figure 4-2: Steam network for the simulated sugarcane mill with a crushing rate of 250-tonnes per hour and steam consumption of 400 kg per tonne of crushed cane.

Approximately 58% of the available bagasse is used as fuel in the boiler to produce high-pressure steam while 41% is the surplus bagasse for potential use in renewable electricity and bioproducts production. The remainder consists of fine bagasse particles (bagacillo) which are used as a filter aid. When the process steam demands are more than the available exhaust steam, additional HP steam is produced and passed to a let-down valve and de-superheating station to be reduced to the process steam range requirements. A portion of the vapor produced from the evaporation of water in the juice of the first to third evaporator effects is extracted for use in the extraction, clarification, and crystallization unit. The more the number of evaporator effects and the extent of vapor bleeding, the more the energy-savings. However, capital, technical, and potential energy improvements must be considered [18].

Table 4-1: Base case operating conditions and configuration of the simulated sugar mill factory

Cane throughput	250 tonnes/hr
Cane composition	14.17 % sucrose;15.06% fiber ;16.41% dissolved solids
Tonnes imbibition water/bagasse tonne fiber content	295 %
Bagasse moisture content	51%
Total number of effects	5
LP exhaust steam distribution	[Clear juice preheater, 1st effect, sugar drier air heater]
Clear juice inlet concentration	13.68 °Bx
Clear juice inlet temperature to 1st effect	112.52℃
Clear juice flow	281.67 tonnes/hr
Syrup dissolved solids (DS) concentration	64.82 °Bx
Last effect vapor temperature	58.7 ℃
Condensate flash position	2nd to 5th effect
Heat transfer area in m^2	[2628.6, 1962.6, 580.7, 1998.7, 2133.2]
Heat transfer coefficients in $W/m^2.K$	[2995, 2214, 1858, 1099, 598]
Evaporator pressure distribution, in bar	[1.60, 1.25, 0.60, 0.40, 0.16]
Evaporator feed flow sequence	Forward
Vapor bleed 1 (113.7℃)	
Tertiary clarification unit heat exchanger	5.72 tonnes/hr
Press water heater	0.88 tonnes/hr
Diffuser direct injection	4.19 tonnes/hr
A-pan	20.14 tonnes/hr
B-pan	6.04 tonnes/hr
Vapor bleed 2 (106.5℃)	
Secondary clarification unit heat exchanger	10.06 tonnes/hr
Diffuser heater	8.65 tonnes/hr
Re-melter	0.36 tonnes/hr
C-pan	2.46 tonnes/hr
Vapor bleed 3 (86.4 ℃)	
Primary clarification unit heat exchanger	7.26 tonnes/hr
Water evaporated in A-pan	17.98 tonnes/hr
Water evaporated in B-pan	5.49 tonnes/hr
Water evaporated in C-pan	2.10 tonnes/hr
Total raw sugar produced (A-sugar)	28.86 tonnes/hr

4.2.3. Disturbances responsible for excess energy consumption

During operation, a sugar factory must satisfy several constraints imposed by its design configuration and socio-economic conditions, in the presence of external and internal disturbances. In this study, the disturbances of interest are those with an influence on the energy efficiency of a sugar mill. From the review of the literature, the disturbances responsible for the instigation of steady-state operational deviations in the sugar mills were identified. These fall into four main categories namely the (i) external disturbances [18], (ii) internal disturbances [9] (iii) overall equipment efficiency and (iv) plant personnel [10].

The external disturbances in the sugar mill are mainly caused by field-related issues like cane growth, harvest, and transportation which influence the cane quality, quantity, and supply consistency. While internal disturbances are associated with operational variations emanating from process activities like product reprocessing, inadequate water removal, excessive water addition, and other ineffective operational practices. Overall equipment efficiency relates to the capability of the equipment to achieve its production goal effectively and how deviations from this goal influence the energy balance of the factory. The final category emphasizes the necessity of standard operating procedures which include both production and energy-efficient practices.

From the literature review and the acknowledgment of the MATLAB sugar mill model limitations, eight variables were chosen to represent these classes of disturbances and their quantitative influence on the energy outlook of the sugarcane factory. These consist of:

i. The amount of imbibition water used in the extraction unit (IW) is a function of the cane fiber content.

ii. The syrup dissolved solids concentration (SB) shows the adequacy of water removal.

iii. The extent of A, B, and C-massecuite recycling in the crystallization unit as a function of the A, B, and C-massecuite dry substance concentration (RECA, RECB, and RECC).

iv. The A, B, and C-massecuite temperature in the vacuum pans (VPA, VPB, and VPC)

4.2.4. Definition of energy indicators

The evaporation unit is responsible for concentrating the juice from approximately 13 to 65°Bx. This comes with a significant amount of energy consumption because of the high latent heat of water vaporization and the large quantities of water to be evaporated. Therefore, the evaporation unit energy indicator is defined in such a manner that the amount of effectiveness of LP steam usage in attaining the target syrup DS concentration through water evaporation is determinable. Despite the energy benefits of the multiple effect evaporators, the steam economy of the evaporator unit is largely influenced by the variations in the dependent process units like the crystallization unit. The coupling of the crystallization unit with the evaporator unit through pan vapor requirement has been reported as the main cause of long oscillatory perturbations in the evaporator unit [21]. Therefore, the energy monitoring of the crystallization unit is considered essential. Water is added to the crystallization unit to dilute molasses, dissolve false grains, wash out pans, clean up C sugar magma, regulate movement, or as balancing water and wash water in the centrifuges [22]. The use of water in the crystallization unit represents additional water that must be evaporated by the application of process energy, in addition to the water already present in the syrup from the evaporation unit. In this regard, the energy indicator in the crystallization unit was also defined as the vapor consumed per tonne of water evaporated.

To acquire insight into the overall energy consumption perspective of a sugar mill, a factory level energy indicator was defined. The main input and output streams in the sugar process system are the cane and the raw sugar produced, respectively. Therefore, two factory level energy indicators were defined to determine the overall steam consumed per tonne of cane crushed and raw sugar produced. The list of the defined energy indicators is given in Table 4-2.

Table 4-2: Formulas and steady-state values of the defined process and factory level energy indicators

Process Unit	Defined Energy Indicator	Units
Evaporation Equation (4-1)	$\frac{\dot{m}_{LP\ steam,in} \times (h_{LP\ steam\ in,} - h_{LP\ steam,condensate})}{\dot{m}_{Evap:\ water\ evaporated}}$	kWh/kg water evaporated
Crystallization Equation (4-2)	$\frac{\dot{m}_{pan\ vapor,in} \times (h_{pan\ vapor,in} - h_{pan\ vapor\ ,condensate})}{\dot{m}_{Crys:\ water\ evaporated}}$	kWh/kg of water evaporated
Overall steam consumed Equation (4-3)	$\frac{\dot{m}_{HP\ steam} \times (h_{HP\ steam} - h_{boiler\ feed\ water})}{\dot{m}_{cane\ crushed}}$	kWh /a tonne of cane crushed
Overall steam consumed Equation (4-4)	$\frac{\dot{m}_{HP\ steam} \times (h_{HP\ steam} - h_{boiler\ feed\ water})}{\dot{m}_{raw\ sugar}}$	kWh /a tonne of sugar produced

4.2.5. Development of the predictive energy models

A two-step approach consisting of sensitivity and statistical analysis is used in the development of energy models for energy monitoring, predicting, and targeting in sugarcane mills.

4.2.5.1. Sensitivity studies

From the review of the published literature, the typical value variations of the 8 selected variables were determined. The typical lower and upper steady-state value deviations of the 8 variables which are used for this study are given in Table 4-3. The typical values for the imbibition water, syrup DS concentration, and massecuite recycling was attained from [23]. The upper and lower massecuite temperature ranges were considered as a $\pm 6\,℃$ temperature deviation from the massecuite temperature values used in the steady-state MATLAB sugar mill model [19].

Table 4-3: Parameter levels for sensitivity analysis

Key Variables	Parameter Levels		Units
	Low	High	
Imbibition water	2.50	4.00	Tonnes of water/tonne of bagasse fiber
Syrup DS concentration	60.00	70.00	°Bx
Recycling in A-pan	88.00	92.00	% Dry substance content of A-massecuite
Recycling in B-pan	90.00	94.00	% Dry substance content of B-massecuite
Recycling in C-pan	92.00	96.00	% Dry substance content of C-massecuite
A-massecuite temperature	61.00	73.00	℃
B-massecuite temperature	61.00	73.00	℃
C-massecuite temperature	61.00	73.00	℃

To observe the energy patterns in sugar mills with the ingress of disturbances, the disturbances must be modeled into the existing steady-state MATLAB sugarcane model. For this study, the steady-state value deviations of the selected variables were used to obtain a representation of the disturbance influence on the energy tends. Therefore, to investigate the parameter steady-state value variation effect on the energy consumption of a sugar mill, a new code was integrated into the existing MATLAB sugar mill model. The developed code for the sensitivity studies consists of three main parts namely:

i. The first part uses the statistical toolbox of the MATLAB model to develop a full factorial design matrix of the 8 variables at two levels. The full factorial design was chosen as it allows the effect of an individual parameter on the response variable to be evaluated at several levels of the other variables considered in the study [24]. This yields conclusions that are valid over a wide range. This makes it possible to evaluate the impact of 256 (2^8) combinations of these parameter values on the energy indicators.
ii. The second portion of the code integrates the full factorial design matrix of the operating variables to the embedded MATLAB sugar mill model.
iii. Finally, the output of the sensitivity studies is displayed based on the written code for the defined energy indicators to highlight the influence of parameter variation on the steady-state energy consumption perspective of a sugarcane factory.

4.2.5.2. Statistical analysis

The Statistica® 13.2 software was used to conduct statistical analysis of the normalized 2^8 sensitivity design matrix results from the MATLAB sugar mill model. Statistical analysis is a strategized procedure for analyzing the data obtained from conducting simulation-based sensitivity studies. Analysis of Variance (ANOVA) is used to screen for the key variables whose steady-state value variation significantly influences the energy response of the system. A significance level of 0.05 (p=0.05) has been used. To establish the relationship between the significant operating variables and the energy response, a regression model is fitted to the observed data means. The scalar notation of the fitted regression model is expressed in Equation (4-5). Where Y represents the defined energy indicators, β_0 is the unknown estimate mean of the energy response, x_i is the key operating parameter, β_i and β_{ij} are the unknown estimates of the main and interaction effects respectively.

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \sum \beta_{ij} x_i x_j + \in; \qquad \in \sim N(0, \sigma^2) \tag{4-5}$$

4.3. Results and discussion

4.3.1. Evaporation unit

The steady-state value of the evaporator unit energy indicator defined in Equation (4-1) is 0.232 kWh/kilogram of water evaporated. Through the statistical analysis of the 256 combinations of the 8 selected variables, the significant variables whose steady-state value deviations lead to the largest change in the energy indicator steady-state values, were determined. The ordered list of the variables and their interactions that produced the highest standardized and percentage effect on the evaporator index is given in the Pareto chart in Figure 4-3.

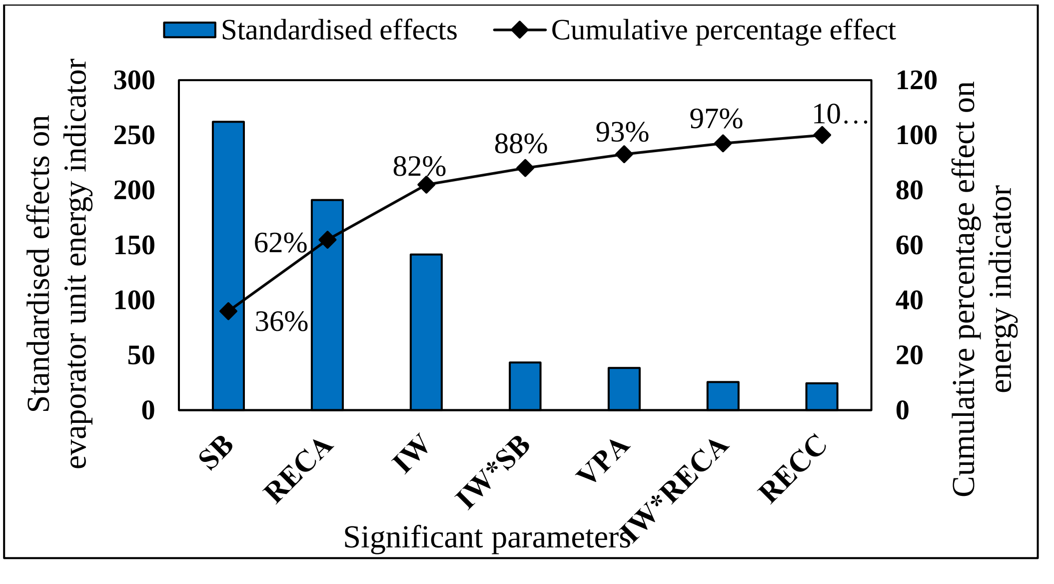

Figure 4-3: Standardised and cumulative effects of key variables on the evaporator energy indicator

Of the eight variables investigated in this study, the steady-state deviations in the syrup DS concentration, A-massecuite dry substance concentration, and imbibition water are responsible for an 82% cumulative influence on the evaporation unit energy indicator value. The goal of the evaporator unit is to produce the target syrup DS concentration at minimal energy consumption. In accomplishing this goal, the process inputs, outputs, and disturbances need to be identified. The work by [21] aimed at improving the control architecture of evaporators in a sugarcane mill identified the pan vapor demand, inlet juice concentration, and flow as the main disturbances influencing the evaporator unit steam economy. The amount of imbibition water used influences the inlet clear juice flow and concentration. On the other hand, the syrup DS concentration, and the extent of massecuite recycling determine the pan vapor demand. Therefore, the current study has further contributed to the available literature by identifying a set of key variables to monitor and target at desired set-points to suppress the inlet clear juice concentration and pan vapor demand disturbances in the evaporator unit.

4.3.1.1. Development of the predictive energy model for the evaporator unit

To establish the relationship between the key variables and the evaporation unit energy response, a linear regression model was fitted to the observed data means. The statistically developed linear regression model in $\mathrm{kWh/kilogram\ of\ water\ evaporated}$ is denoted by Equation (4-6). The notation $\mathrm{EI_{evap:\,predicted}}$ represents the predictive evaporator energy indicator.

$$\begin{aligned}\mathrm{EI_{evap:predicted}} = {} & 0.97 - 0.098\ \mathrm{IW} - 0.0036\ \mathrm{SB} - 0.0058\ \mathrm{RECA} + \\ & 0.0004\ \mathrm{RECC} + 0.0002\ \mathrm{VPA} + 0.0005\ \mathrm{IW} \times \mathrm{SB} + \\ & 0.0007\ \mathrm{IW} \times \mathrm{RECA}\end{aligned} \tag{4-6}$$

The predictive energy model represented in Equation (4-6) has an R-squared (R^2) value of 0.988. This indicates that there is less variability between the observed energy values from the MATLAB sugar mill model using Equation (4-1) and those that are calculated using the predictive energy model in Equation (4-6). Hence the statistically developed model equation can be used to predict the energy trends of the evaporator unit systems in a sugar factory by measuring and monitoring these fundamental variables. The regression coefficient value of the energy predictors will depend on the number of effects and the configuration of the vapor bleeds. Therefore, this index is more suitable for internal energy benchmarking or external benchmarking of sugar mills with comparable configurations. Literature studies have suggested a range of energy measures for energy reporting and benchmarking in sugarcane mills. These measures of energy can be sub-divided into:

i. Factors contributing to energy demands [18].
ii. Absolute measures of flow can be translated to energy consumption information, for example, kWh of electricity used or exported. This is only useful for internal benchmarking and energy monitoring [9].

iii. Energy utilization indices show the consumption of energy as a function of important input or output streams. For example, MJ per tonne cane crushed [11].

As compared to previous studies, this study has combined all these concepts to propose two energy indicators for gauging the energy performance of the evaporator unit. The first proposed evaporator energy indicator (Equation (4-1)) is defined as the absolute measure of low-pressure steam flow to the first evaporator effect to attain the desired water evaporation. The second energy indicator (Equation (4-6)) is an energy prediction and targeting tool based on the variables whose steady-state offsets results in excess energy demands in the evaporator unit. Energy intensity indicators like the vapor bleed % LP steam and HP steam % cane have been previously defined for the evaporator unit in sugar mills [10]. Although these indices are good for energy reporting, they lack adequacy in showing the contributing parameter to observed changes in the energy indicator value. This is considered necessary for strategized root-cause analysis in a system consisting of many process unit interlinkages as those found in the sugarcane mills. Therefore, using this mixed approach and the illustration of methods for developing predictive energy models, this study strengthens the existing literature.

4.3.1.2. Main effects in the evaporator unit

Effect of syrup dissolved solids concentration

The syrup DS concentration has the highest effect of 36% on the evaporator energy response as shown in Figure 4-3. The syrup produced in the evaporation unit is directed to the crystallization unit where it is split between the A-pan and the mingler. Due to the re-use of the steam latent heat in the multiple effect evaporators, the evaporation efficiency in the evaporator station is higher than for pans, which are single heating units. The additional amount of water in low syrup DS concentration flows to the crystallization unit and the low pan evaporation efficiency leads to increased vapor demands in the crystallization unit. For the evaporator unit to sustain the elevated vapor demands, the LP steam flow and pressure to the first effect are increased. Hence the observed change in the evaporator unit energy indicator with variations in the syrup DS concentration.

The exergy work done by [8] identified the A-pan as having the highest irreversibility in the crystallization unit. This is attributed to the high-water evaporation load in the A-pan. The energy impact of the A-pan water evaporation load can be deduced from the large effect of the syrup DS concentration on the evaporator unit energy indicator. Therefore, it is recommended that the allowable maximum water evaporation is achieved in the evaporation unit to avoid the excess vapor demands and irreversibility associated with high water evaporation loads in the A-pan. The control of the dissolved solids content of the remelt stream to the A-pan is urged.

By shifting the syrup DS concentration operational set-point in the simulated sugarcane mill from 60 to 70 dissolved solids concentration, there is a 0.02 decrease in the energy used per kilogram of water evaporated. This efficiency improvement corresponds to a 1.5 % decrease and a 2.3 % increase in the LP steam used and final effect vapor per tonne of cane, respectively. The increase in final effect vapor is a result of the pronounced reduction in the pan vapor bleeds demand from the evaporator unit. This represents an additional energy-saving opportunity for the factory through optimal retrofit design and vapor bleed re-configuration in the evaporator unit using the aid of pinch techniques. Maximizing the use of the vapor bleed streams from the last evaporator effect minimizes the final effect of vapor flow to the condenser. For effective use of the last effect vapor bleed streams, the pressure profile in the evaporator unit must be raised. However, the limit of these energy-saving measures is that when a factory is already operating at maximum syrup DS concentration any further increment in the vapor bleed demand will have to be met by letting down an equal amount of LP steam to the vapor operating range. Hence, for an existing plant, the technical and economic feasibility analysis of these measures is required, considering disturbances like cane quality. An illustration of such analyses is provided in [25].

Effect of Imbibition Water

Elevated imbibition water use leads to increased energy requirements in the evaporator unit. The amount of imbibition water has a negative coefficient in the developed evaporator unit energy model meaning that an increase in imbibition water will lead to a reduction in the defined energy indicator. This interpretation is a function of how the energy indicator was defined as a ratio of the LP steam used in the first effect on the total water evaporated in the evaporator unit. For example, a shift from 2.5 to 4-tonnes imbibition water per tonne of bagasse fiber content results in a 27% and 23% increase in the total water evaporated and the LP steam consumed, respectively. Hence, the observed decrease in the energy indicator value at high imbibition water is due to the differences in the magnitude of increase for the LP steam flow and total water evaporated. The LP steam increases due to increased evaporation load, extraction, and clarification vapor bleed demands.

Effect of A-massecuite recycling and A-massecuite temperature

The A- massecuite temperature deviations from 60℃ to 70℃ correspond to a change in pan operating pressures from 12.2 to 18.3 kPa (abs) and an estimated 1℃ boiling point elevation at saturation points for massecuite purities of 90% [18]. Therefore, these changes in boiling conditions in the pan explain the observed increase in the evaporator energy index at high A- massecuite temperatures. The arguments in favor of vacuum operation are that the liquid boiling temperatures in the pans are reduced while minimizing the energy demands and sucrose inversion losses in the unit. On the other hand, the change in percentage massecuite dry substance concentration from 92 to 88 corresponds to an increase in A-massecuite recycling from 0.86 to 1.2 massecuite volume (m3) per tonne dissolved solids content of mixed juice. Hence a shift from a dry substance concentration of 92 to 88 % leads to a 28% increase in A- massecuite recycling. At low A- massecuite concentration, the quantity of sucrose dissolved in the molasses recycled to the subsequent pan stages (B and C pan) is increased. The study results indicate a 5.5% increase in the defined evaporator index for a 28% increase in A-massecuite recycling.

An increase in A- massecuite recycling and temperature increases the pan vapor requirement which affects the pressure profile and energy efficiency of the evaporator unit. Published data from an Australian sugar mill showed that the pan vapor demand disturbances are responsible for the longest sustained oscillatory perturbation in the evaporator unit [21]. Therefore, further analyses were conducted to evaluate the influence of A-massecuite temperature and dry substance concentration on the pan vapor demand as shown in Figure 4-4.

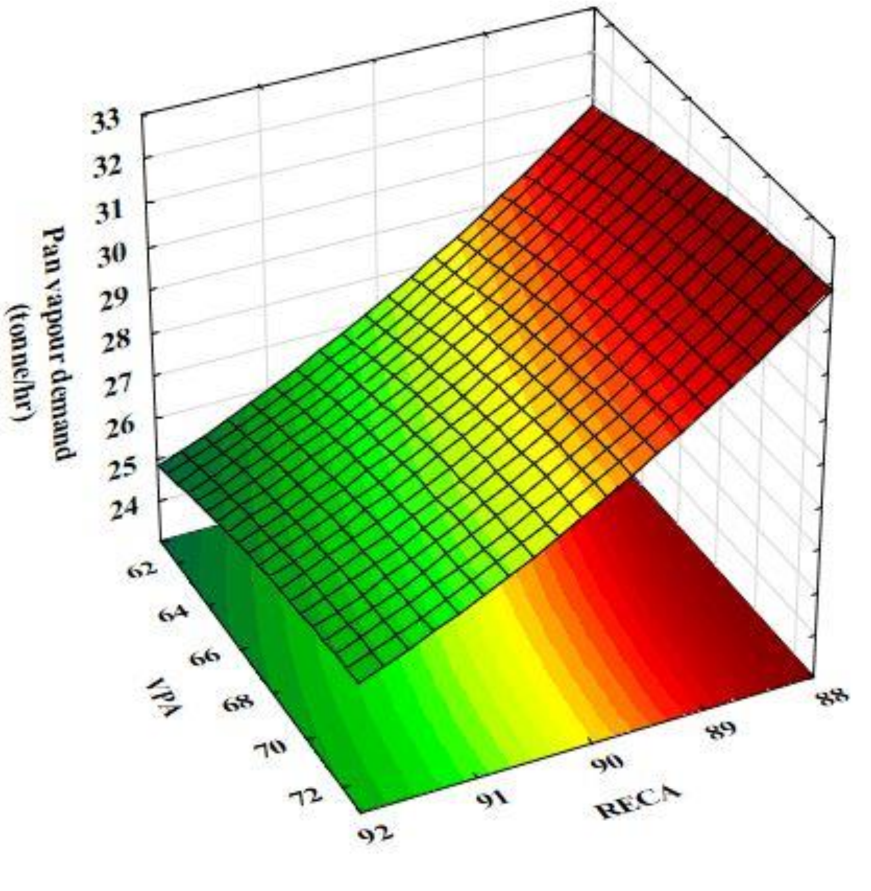

Figure 4-4: Surface plot illustrating the effect of A-massecuite dry substance concentration (RECA) and temperature (VPA) on the overall pan vapor demand

There is a decrease in the pan vapor demand when a high A-massecuite dry substance concentration (greater than 92%) and lower A-massecuite temperature (below 66℃) is attained. The recommended parameter ranges from the statistical results agree with those reported by [18]. Calculations show that a shift in the A- massecuite dry substance concentration from 88 to 92% and temperature from 73 to

61°C lead to approximately 19% and 4% reduction in the pan vapor demand. Hence if the two predictors, the reduction of massecuite recycling is more essential in reducing pan vapor demand fluctuations.

Effect of* C-massecuite *recycling

A decrease in the attained C-massecuite dry substance concentration results in a reduction in energy demands. This is because, at low C-massecuite dry substance concentrations, there is less production of the C- sugar to be dissolved in the re-melter and recycled back to the A-pan. This decrease in the pan and re-melter feed and hence vapor requirements results in reduced energy demands from the evaporator unit. However, this scenario leads to an increase in the C-molasses stream and hence the corresponding factory sucrose losses. Figure 4-5 shows the effect of C-massecuite dry substance concentration on the evaporator energy index and the sucrose content in C-molasses. A 2% decrease in C-massecuite dry substance concentration results in a 0.3% decrease in the evaporator unit energy index and a 1-3% increase in the sucrose lost in the C-molasses stream. Therefore, a trade-off between energy and production efficiency based on the monetary energy benefits and sugar revenue is required.

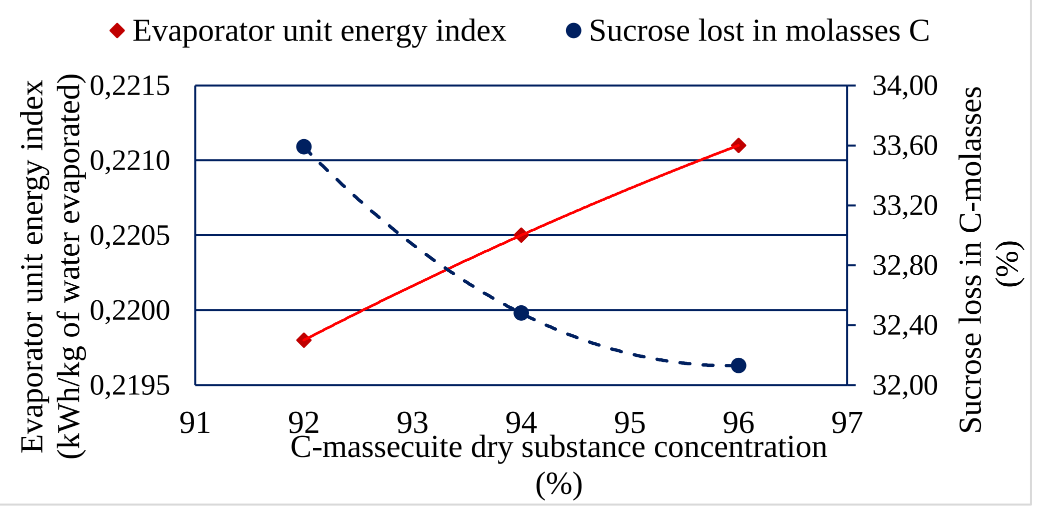

Figure 4-5: Effect of C-massecuite dry substance concentration on the evaporator unit energy indicator and C-molasses sucrose loss

4.3.2. Crystallization unit

Figure 4-6 is a Pareto chart showing the cumulative and standardized effects of the main energy influential variables whose steady-state deviation leads to the largest change in the defined crystallization unit energy index (Equation (4-2)). For the simulated sugarcane mill, the steady-state value of the crystallization unit energy indicator is 0.692 kWh/kilogram of water evaporated. The massecuite temperature in all three pans, massecuite recycling in A and B batch pans are responsible for a cumulative effect of 92% on the defined crystallization unit energy indicator. Therefore, of the eight variables considered in this study, these five are the main variables to focus on in the crystallization unit.

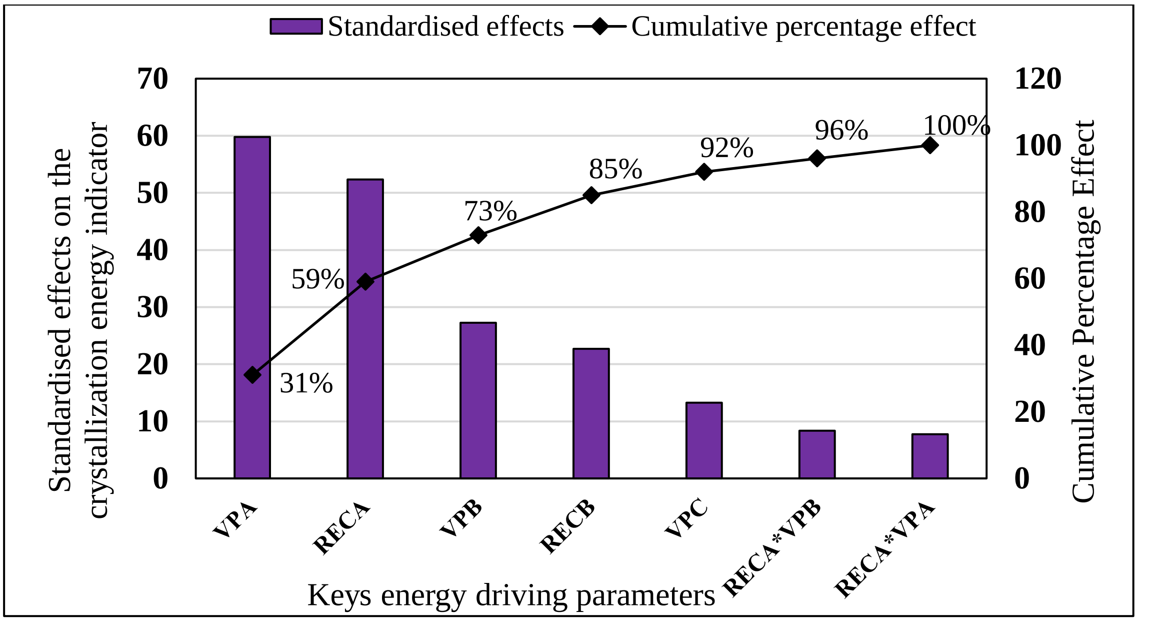

Figure 4-6: Pareto chart of standardized effects in the crystallization unit energy indicator

A linear regression model was fitted to the observed data means to develop an energy model for predicting the crystallization unit energy indicator value based on these 5 major energy-influencing variables. The developed energy model is given in Equation (4-7) has a coefficient of determination R-squared of 0.96. The notation $\mathrm{EI}_{\mathrm{crys:\,predicted}}$ represents the predictive crystallization unit energy indicator in kWh per kg of water evaporated.

$$\begin{aligned}\mathrm{EI}_{\mathrm{crys:predicted}} = {} & 1.838 - 0.014\ \mathrm{RECA} - 0.016\ \mathrm{RECB} + 0.002\ \mathrm{VPA} - 0.008\ \mathrm{IW} \\ & + 0.001\ \mathrm{VPB} + 0.0004\ \mathrm{VPC} - 0.0007\ \mathrm{SB} + 0.00017\ \mathrm{RECA} \times \mathrm{RECB}\end{aligned} \tag{4-7}$$

4.3.2.1. Main effects in the crystallization unit

The A-massecuite temperature was observed to have the highest effect of 31% on the vapor demands of the crystallization unit (Figure 4-6). A shift in massecuite temperature is related to a change in the pan pressure due to the vapor-liquid equilibrium. At high A-massecuite temperatures, the vapor flow of higher pressure is required to increase the temperature driving force and maintain the same heat flux. Significant sucrose inversion losses can occur in the crystallization unit at high massecuite temperatures. The A-pan had the highest irreversibility of 59% in the crystallization unit based on the exergy work conducted by Dogbe et al. [8]. The conducted exergy work was based on the same data input as that used in the MATLAB sugarcane mill model. The high irreversibility in the A-pan is a consequence of the large temperature difference required for heat transfer [8]. Therefore, the monitoring and targeting of low A-massecuite temperature (VPA) are suggested strategies in this study for ensuring the improvement in the A-pan energy demands, production efficiency, and irreversibility.

Continuous pans can significantly improve the steam economy of the factory as they utilize vapor flows of lower pressure while relying on natural circulation. Rein [18] quotes the required temperature difference between the vapor in the calandria and the boiling mixture to be over 40 °C for batch pans to achieve reasonable boiling times while continuous pans can be operated at temperature differences of 25 to 40 °C. Therefore, from a design perspective, it can be argued that using continuous pans rather than batch pans has the potential in improving both the energy efficiency and the irreversibility of the crystallization unit.

From the developed energy model, a change in A-massecuite dry substance concentration from 92 to 88% leads to an increase in vapor used from 0.68 to 0.69 kWh/kg of water evaporated. Thus, there is a 2% increase in the crystallization index for a 28% rise in A-massecuite recycling. This increase in pan vapor requirements results in more LP steam flow to the evaporator unit to enable the generation of sufficient vapor flow and heating pressure for the crystallization operations. This notion is observed from the 5.5% increase in the evaporator energy index at a 28% increase in massecuite recycling. From the changes in the evaporation and crystallization unit energy indicator values, it can be deduced that the effect of massecuite recycling is more pronounced in the evaporator unit than in the crystallization unit. Hence, it is considered important to maintain low A-massecuite recycling rates for the energy-efficient operation of both the crystallization and evaporation units.

Achieving high A-massecuite exhaustion reduces the extent of A-molasses recycling to the B and C pans which is crucial for decreasing the water evaporation load and vapor demands in these pan stages. According to the work by [8], the B and C pans contributed 19% of the irreversibility in the crystallization unit. Irreversibility is affected by the product size, therefore, based on the present study results, the water evaporation load of the B and C pans can be improved by attaining high A-massecuite dry substance concentration (RECA). The strict control of the re-melt dissolved solids concentration and shorter pan steaming out procedures are amongst some of the operational strategies to consider for high massecuite exhaustion [18].

4.3.3. Overall steam consumption

Design features such as the number of evaporator effects, vapor bleed configuration, prime movers, and energy reduction schemes used, determine the amount of HP and LP steam required for the manufacturer of raw sugar. In certain instances, the raw sugar mill can be annexed to a raw sugar refinery, hence there might be an export of HP steam to the refinery processes. In this study, the factory level energy indicators were defined to provide a broad view of the amount of HP steam used in the raw sugar processing system to process a unit mass of cane or produce raw sugar. Considering two factories where one only produces raw sugar and the other is annexed to a raw sugar refinery. To conduct external energy benchmarking of these two factories based on the defined energy indicators (Equation (4-3) and (4-5)), any electricity or HP steam exported to the annexed processes has to be excluded and only HP steam used solely for raw sugar production considered.

Simulation-based sensitivity studies were conducted to determine the influence of the 256 different operating conditions due to the steady-state deviations of the eight selected variables on the defined factory-level energy indicators. The Pareto analysis was used to identify the most influential variables in the overall factory energy consumption perspective. The data obtained from the sensitivity studies were fitted into linear regression models for predicting the kWh ⁄ tonne of sugarcane crushed and kWh /tonne of sugar produced based on the identified key variables. The standardized percentage effects of the key variables and the developed predictive models are given in Table 4-4.

Table 4-4: Percentage effect of the key variables and developed energy prediction models

Defined energy indicators	Predictive model / Percentage effect	Mean	IW	SB	RECA	RECC	VPA	VPB
$\frac{kWh}{tonne\ of\ cane}$	Model equation (4-8)	651	36.94	-1.36	- 4.76	0.29	0.50	
	Effect (%)		59	15	20	2	4	
$\frac{kWh}{tonne\ of\ sugar}$	Model equation (4-9)	7441.61	319.44	-10.41	- 48.77	-9.05		2.82
	Effect (%)		56	12	23	4	-	4

4.3.3.1. Main effects in the overall factory steam balance

The amount of imbibition water used, the syrup DS concentration, A, and C massecuite recycling affect both the overall steam consumed per tonne of cane crushed and sugar produced. The A-massecuite temperature only affected the HP steam consumed per tonne of cane crushed while B-massecuite temperature affected the HP steam consumed per tonne of sugar produced. On the other hand, B-massecuite recycling and the C-massecuite temperature had an insignificant effect on the overall steam balance as compared to the other tested variables.

Effect of high imbibition water use in the extraction plant

Of the variables tested, imbibition water had the highest effect of 59% and 56% on the kWh used per tonne of the cane crushed and sugar produced, respectively. The amount of imbibition water used in the extraction plant is a significant variable that affects the overall energy balance and the sucrose extraction efficiency of a sugar mill. As the quantity of imbibition is elevated, sucrose extraction efficiency increases. However, as shown in Figure 4-7, moving from a set-point of 2.5 to 4 tonnes imbibition water per tonne of bagasse fiber leads to a 15% and 27% increase in the vapor bleed demand and total water to be evaporated in the evaporator unit, respectively. To maintain the same temperature of the draft juice at elevated juice flow, more vapor bleed is admitted to the extraction unit. Similarly, more vapor flow and pressure is required in the clarification unit heat exchanger train to sustain the increase in juice flow and maintain the same heat flux to the mixed juice.

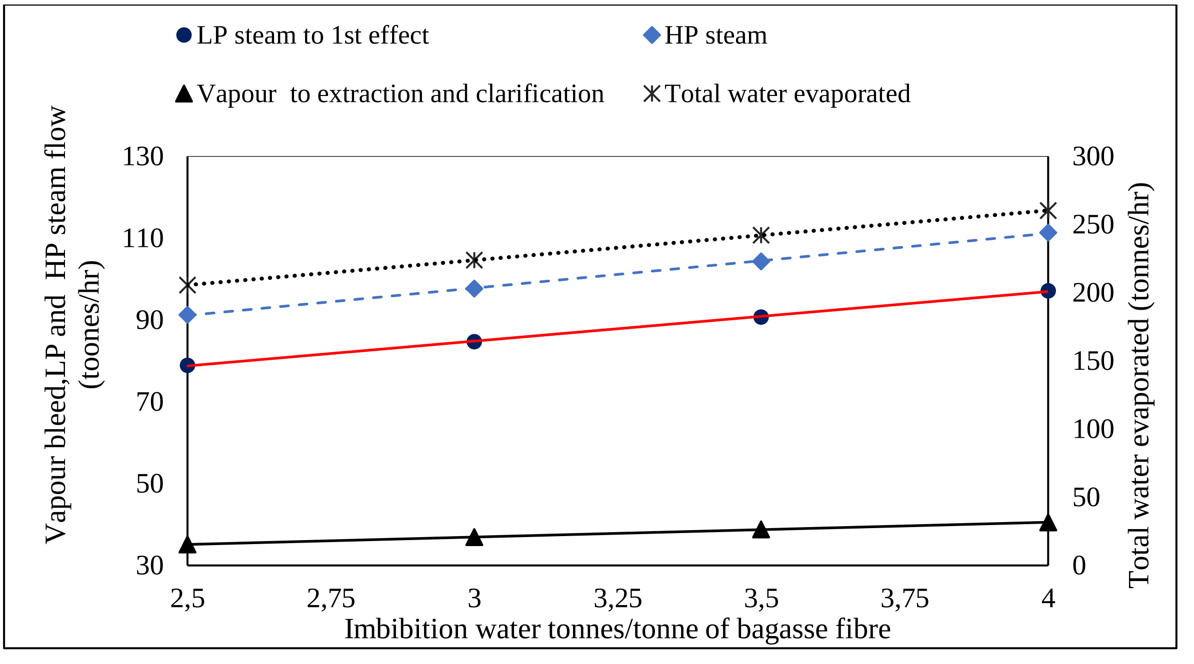

Figure 4-7: Effect of imbibition water on total water evaporated, vapor bleed, LP and HP steam demands

These variations due to elevated imbibition water lead to increased fuel demand in the boiler unit to generate the additional 23% HP steam required to accommodate the increased energy requirements in the evaporator unit. Poor can preparation and high cane fiber content result in the need for more imbibition water to achieve the desired sucrose extraction. Although the cane quality variations are inevitable, cane preparation can be improved by using heavy-duty shredders with minimum knifing to avoid short the cane fiber length. Cane preparation is measured using bulk density, mean particle size, or the extent of cell breakage [18].

Effect of A and C massecuite dry substance concentration

The A-massecuite dry substance concentration had the second observed highest effect on the defined overall factory energy indicators. An increase in A-massecuite dry substance concentration leads to reductions in the A-massecuite quantities and hence reduced overall recycling, sucrose inversion losses, steam requirements in the evaporator, and crystallization unit. Thus, high A-massecuite exhaustion is essential for reducing the overall factory steam demand. At low C-massecuite concentration, less C-sugar and more C-molasses is produced. Hence the decrease in HP steam demand per tonne of the cane is a result of the reduced re-melt and A-pan vapor demands at low C-massecuite dry substance concentration. A reduction in C-sugar means that there are high sucrose losses in C-molasses exiting the factory. A decrease in C-massecuite dry substance concentration from 96 to 92% results in a 1.5% reduction in the overall sucrose recovery. This effect of C-massecuite dry substance concentration on sugar recovery is not captured in the overall factory index defined as a function of cane throughput. However, the second factory level index, HP steam consumed per tonne of sugar produced, can take into account this effect as observed by the negative coefficient for C-massecuite dry substance concentration in Equation (4-9). It is important to acknowledge that energy monitoring does not imply curtailing production. The use of kWh/tonne of cane alone might be misleading. Both energy indicators offer different attributes hence their collective use is recommended to provide information for determining the trade-off between energy and production efficiency.

Effect of syrup DS concentration, A and B massecuite temperature

The observed increase in HP steam consumed per unit mass of cane or sugar produced at low syrup DS concentrations is a result of the increased pan vapor demands. A set of control objectives that must be fulfilled to secure high and stable syrup DS concentration during operation is provided in [26]. In the present study, the acquirement of more precise sensors for syrup DS concentration measurement is recommended. A precise sensor provides a high degree of agreement among consecutive measurements of a fixed variable value. This is an important aspect when the desired operational condition lies closer to the safety or production limits. Hence to enable confident operation at the desired conditions while complying with the safety and production constraints, the utilized sensor must provide precise readings of the measured variable of interest. For example, a precise sensor for syrup DS concentration measurement can enable a factory to operate at higher concentration levels closer to the saturation point at which crystallization commences while tapping into the energy benefits of such operating conditions.

High A and C-massecuite temperatures lead to elevated steam consumption per tonne of cane and sugar produced, respectively. The vacuum pressure in A and B pan need to be maintained high to achieve high evaporation rates and avoid elevated massecuite temperatures. Lower massecuite boiling temperatures also allow for the effective use of the vapor bleed from the evaporator unit. If the vacuum is low and the massecuite temperature too high, checks for possible air ingress into the pans or through the product, and cooling water streams are required. The use of ultrasonic detectors is suggested for efficiently identifying the pan air leaks. For absolute pressure control in the pans, the use of the absolute pressure transmitters is preferred as compared to the vacuum transmitter [18]. This ensures that the boiling temperatures in the vacuum pans are not influenced by changes in the atmospheric pressure.

4.4. Suitability of the defined and developed energy indicators

4.4.1. Sensitivity test of the developed energy prediction models

To this end, this study has aimed to propose suitable energy indicators for use in excess energy consumption monitoring, mostly due to operator actions or process variations. To test the suitability of the proposed energy models for use during unsteady-state operation in the factory, two disturbances were considered namely the seasonal cane quality variations and the decrease in heat transfer coefficients (HTC) due to evaporator tube fouling. When there is fouling of the evaporator tubes, the thickness and low thermal conductivity of the scaling deposits imposes an additional resistance to heat transfer [18]. This leads to lower HTCs for fouled tubes as compared to clean vessel tubes. The deteriorating heat transfer coefficients result in increased LP steam flow and pressure to the calandria to increase the temperature driving force and maintain the same heat flux to the juice. An increase in steam pressure leads to a decrease in the latent heat of condensation thus a portion of the increase in steam flowrate accounts for this aspect. The energy models were validated for different evaporator unit heat transfer coefficients as a function of tube scaling with time. The evaporator vessels are often scheduled for cleaning after two or three weeks of operation. Hence, the test was done for two scenarios namely, time = 0 when the evaporator vessel tubes are clean and at time= 3 weeks accumulation of scaling deposits in the evaporator tubes. The heat transfer coefficient values in Table 4-1 were used for the clean evaporator unit vessels and those for 3 weeks were calculated based on the scaling factor values in [27] for typical quintuple Robert evaporators.

The variation in the quality of cane has been accredited to several factors, ranging from the genetic potential of the cultivars, climate conditions, and agricultural management. Variability in the cane quality during the milling season results in significant constraints on the sugar mills' production system. The non-sucrose and the fiber constituents of cane all come into effect during the milling season. The amount of imbibition water used in the extraction plant is correlated to the cane fiber content. An increase in the cane fiber results in elevated use of imbibition water in the extraction plant, increased bagasse sucrose loss while the high non-sucrose content of cane leads to high juice turbidity and poor clarification rates. The energy prediction models were validated for different cane quality values at the beginning and end of the season. The cane sucrose and fiber content values of 12.18 % and 15.53 % were used for the beginning of the season. For the end of the season, the sucrose and fiber content values of 13.14% and 16% were used. The cane quality values were obtained from the 90th Annual Review of the Milling Season in Southern Africa 2014/15 [23]. The observed energy indicator values from the MATLAB sugar mill model were compared with those calculated using the statistically developed energy models to determine the model's prediction accuracy. The energy indicator validation results for cane quality and HTC variation are given in Table 4-5 and Table 4-6, respectively.

Table 4-5: Suitability test of developed energy prediction models at varying cane quality values

	Beginning of season			End of season		
Energy indicators	**Observed value**	**Predicted value**	**% Prediction accuracy**	**Observed value**	**Predicted value**	**% Prediction accuracy**
Evaporation unit **kWh/kg water evaporated**	0.226	0.234	96.31	0.229	0.234	97.67
Crystallization unit **kWh/kg water evaporated**	0.698	0.692	99.14	0.696	0.692	99.43
kWh/tonne cane crushed	296.45	302.81	97.85	300.25	302.80	99.15
kWh/tonne sugar	3386	2576	76.08	2933	2575	87.79

Table 4-6: Suitability test of developed energy prediction models at varying evaporator heat transfer coefficients due to tube fouling

	HTC at time=0			HTC at time = 2 weeks		
Energy indicators	**Observed value**	**Predicted value**	**% Prediction accuracy**	**Observed value**	**Predicted value**	**% Prediction accuracy**
Evaporation unit **kWh/kg water evaporated**	0.232	0.234	98.90	0.24	0.234	97.65
Crystallization unit **kWh/kg water evaporated**	0.700	0.692	98.86	0.691	0.692	99.71
kWh/tonne cane crushed	301.18	302.72	99.49	309.96	302.72	97.66
kWh/tonne sugar	2548	2574	98.97	2622	2574.232	98.18

The developed energy models provided good prediction accuracy of over 95% when used at varying cane quality and different evaporator HTC due to tube fouling. The overall steam used per tonne of sugar used showed lower prediction accuracy values of 76 and 88 % for the cane quality values at the beginning and end of the season, respectively. Although the prediction model for overall steam used per tonne of sugar accounts for sucrose losses in C-molasses through the C-massecuite dry substance concentration there are other sucrose loss streams like the filter cake and bagasse to be considered. Hence, further work is required to develop a more accurate model for Equation (4-4) based on other variables that influence entrainment (e.g. evaporator and pans vapor out velocity) and sucrose inversion losses (e.g. temperature, pH, and retention). Entrainment is the carry-over of juice, syrup, massecuite in the vapor flow exiting the evaporators and pans.

4.4.2. Defined energy indicators as energy benchmarking tools

Energy consumption in a sugar mill is influenced by the design configuration of the factory, implemented operational strategies, and process variations. The prediction energy models in this study were developed from the captured energy trends as a function of parameter steady-state value deviations. Overall, this study managed to illustrate methods for use in developing energy models for online energy monitoring and targeting based on the variables whose steady-state offsets result in excess energy consumption. Through benchmarking within set standards and comparison with other sugar mills, the plant personnel can try to respond to these fundamental questions:

i. What are the alternatives to the present operational targets and practices?
ii. What are the benefits, costs, and risks of the alternatives?

For example, the measured evaporator energy indicator (Equation (4-1)) can be used to benchmark two factories with an N number of effects but with one flashing condensate from one calandria to the next and the other without condensate flashing. For each kilogram of vapor flash added to the calandria from the i^{th} effect condensate, an additional (N-i) kilogram of water evaporated, thereby improving the steam economy. Hence comparing the kWh/kg of water evaporated could be a motivation for the other factory to invest in condensate flash pots and additional evaporator area.

There are many process dynamics and inefficiencies in the sugar mill which influence energy efficiency. The current study focused on the impact of parameter variations on the energy response of the major energy-consuming process units. However, there are other process dynamics and technical inefficiencies which vary with the sugar mills and also for the same factory at varying time or phases but were not taken into account in the present study. Therefore, to identify the impact of these other energy inefficiencies, the benchmarking indices can be defined as the ratio between the predicted energy indicators (Equation (4-6); (4-7); (4-8) and (4-9)) to the corresponding actual measured energy indicators (Equation (4-1); Equation (4-2); Equation (4-3) and Equation (4-4)). This helps to identify whether additional energy was consumed to achieve the production goals. Defining the benchmarking index in a ratio form is preferred as it eliminates the consciousness towards the public sharing of actual energy levels during external energy benchmarking.

The use of predictive modeling eliminates some of the factory dynamics and inefficiencies which are factory and time-dependent. For example, a study by Voigt [28] used linear regression analysis based on real-factory data to correlate the sucrose extraction efficiency to several variables considered important in the operation of the extraction plant. However, the author comments on several unexpected relationships of sucrose extraction with some of the variables. High bagasse moisture content was shown to result in high sucrose extraction while good cane preparation index values affect sucrose extraction [28]. The unexpected correlations in the work by Voigt [28] can be attributed to sampling errors, measurement errors, or the existence of sub-optimal conditions during data collection. Hence the approach used in the present study allowed for better understanding and identification of correlations between energy consumption and the key variables which would have been otherwise impossible based on real factory data and the published literature. To effectively use the method proposed in this present study for the development of energy monitoring indicators based on factory data, the procurement, and availability of precise sensors for the variables of interest is recommended.

4.5. Conclusion

Energy indicators considered useful for gauging the energy performance of a sugarcane factory were defined at the process and overall factory level. A comprehensive and quantitative overview of the key variables whose steady-state value deviation leads to excess energy consumption in sugar mills was done. A 28% increase in A-massecuite recycling was observed to have a pronounced increment of 5.5% on the evaporator unit energy indicator as compared to 2% for the crystallization unit energy indicator. Therefore, the monitoring of the syrup DS concentration, massecuite dry substance concentration, and the temperature is essential in reducing excess energy demands in the evaporator unit related to high pan vapor demands. A 10 unit increase in syrup DS concentration resulted in a 1.5% decrease in LP steam used per tonne of cane and a 2.3% increase in final effect vapor per tonne of cane. The increase in the final effect vapor flow to the barometric condenser represents an additional energy-saving opportunity that can be attained by optimizing the evaporator unit and re-configuring the vapor bleeds. The use of precise concentration sensors and absolute pressure transmitter is urged for control of the syrup DS concentration and pan vacuum operation, respectively. When compared to the other investigated variables in this study, the amount of imbibition water used has the highest effect of 59% and 56% on the overall steam used per tonne of crushed cane and sugar produced, respectively. The suitability of the developed energy prediction models was tested at varying cane quality values and at different heat transfer coefficient values due to evaporator vessel tubes fouling. High prediction accuracies of over 95% were mostly achieved for the developed energy models. Therefore, the methods illustrated in this study for developing energy indicators have potential use in the establishment of an excess energy use monitoring system capable of capturing essential and quantitative information on the main influential variables in the sugar processing system.

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Abbreviations

IW	Imbibition Water
DS	Dissolved solids
HTC	Heat transfer coefficient
HP	High-pressure
LP	Low-pressure
RECA, RECB, and RECC	Massecuite recycling in A, B, and C vacuum pan.
SB	Syrup dissolved solids concentration
VPA, VPB, and VPC	A, B, and C massecuite temperature

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Chapter 5

5. The Determination of Suitable Energy Indicators and Variables for Energy Monitoring of The Boiler Unit in A Sugarcane Factory

This chapter is planned for submission in "Energies"

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The objective of the dissertation in this chapter and the summary of findings

The direct and indirect methods are commonly used to define boiler efficiency. In the direct method, efficiency is defined as the ratio of the steam heat content to the bagasse energy input as fuel. In the indirect method, the sum of all the boiler losses is subtracted from 100 to give the indirect boiler efficiency. Each method has its advantages and disadvantages. The indirect efficiency of the boiler is specified at 100% load. In practice boilers rarely operate at full load conditions, therefore the direct method provides more realistic values for the boiler efficiency. However, 29% of the bagasse energy content was shown (Section 2.2) to be wasted through the boiler heat losses. Hence for understanding and identifying the areas of heat losses, the indirect method is considered more useful. However, in the version of the MATLAB sugarcane mill model used in this dissertation, the boiler configuration is modeled as a simple heat exchanger system. Therefore, to determine the boiler-related variables that influence the indirect boiler efficiency, a standalone cogeneration system modeled in Aspen Plus® is used for this chapter. On the other hand, the improvements in the direct boiler efficiency are investigated in Chapters 6 and 7 based on set-point optimization and optimal sensor placement, respectively.

In the previous chapter objective 1 was addressed for the production units based on the MATLAB model, in this chapter objective 1 is addressed for the boiler unit using an Aspen Plus® simulation. Objective 1 entails the evaluation of the relationships between the controlled variables (CVs) and boiler performance through energy indicator definition and sensitivity analysis. Two energy indicators were defined for the boiler and deaerator system. To provide a good first approximation for the operational economics of the boiler unit while providing a tool for boiler performance monitoring, the economic indicator is defined as the cost of generating HP steam. This cost is dependent upon the unit cost of bagasse, boiler efficiency, the return condensates, and cold-water temperatures and flows, and HP steam pressure. The CVs considered are bagasse moisture content, return condensate temperature, the percentage of cold water used as feedwater, the flue gas temperature, and oxygen concentration. The Aspen Plus® simulation is used to evaluate the effect of CVs variations on the defined energy indicators.

Five percent changes in the bagasse moisture content, flue gas temperature, and excess air were observed to result in 2.36, 0.46, and 0.25 percent changes in the defined boiler energy indicator. For each 2% increase in the percentage of cold water added in the deaerator and a 2˚C drop in return condensates temperature, there is approximately 2.2 kg and 3.1 kg increase in the deaerator steam used per tonne of boiler feedwater. Therefore, the interaction of the boiler system with the extraction unit and evaporator unit through bagasse and feedwater supply significantly governs the operational efficiency of the boiler and the deaerator, respectively. In this regard, for improved boiler and deaerator operation, the adequate control of the dewatering mills in the extraction unit and the reduction of heat losses in the supply of return condensates from the evaporator unit must be prioritized. Moreover, the bagasse moisture content had the largest influence on the HP steam-generating cost, followed by flue gas temperature and oxygen concentration, the return condensate temperature, and lastly, the percentage of cold water used as feedwater.

Declaration by the candidate

With regards to Chapter 5, the nature and scope of my contribution were as follows:

Nature of contribution	The extent of contribution (%)
Project and scope definition, analysis of data, interpretation of results, and writing of chapter	80

The following co-authors have contributed to Chapter 5.

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J.F. Görgens	jgorgens@sun.ac.za	General technical discussions and provided writing assistance through the review of the chapter	5
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Declaration by co-authors:

The undersigned hereby confirm that

1. the declaration above accurately reflects the nature and extent of the contributions of the candidate and the co-authors to Chapter 5

2. no other authors contributed to Chapter 5 besides those specified above, and

3. potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 5 of this dissertation.

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The determination of suitable energy indicators and variables for energy monitoring of the boiler unit in a sugarcane factory

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Abstract

The increasing energy demands coupled with reducing fossil resources have made sugarcane bagasse to be recognized as a key feedstock in the growth of the biofuels and bioproducts industries. As such, to ensure surplus bagasse generation, improvements to the energy efficiency of the boiler operations have become crucial. Therefore, this study aims to identify the boiler unit variables whose steady-state deviations lead to inefficiencies and to define energy (and economic) indicators for energy targeting based on the identified variables. The correlation of the defined energy indicators to the variables with the largest operational influence is considered important for identifying the controlled variables (CVs) requiring precise monitoring and control. The Aspen Plus® cogeneration simulation for a typical sugarcane mill with a cane throughput of 250 tonnes/hr is used to evaluate the effect of CVs variations on the defined energy indicators. The CVs considered are bagasse moisture, return condensate temperature, percentage of cold water used as feedwater, and the flue gas temperature and excess air. The economic indicator is defined as the cost of generating HP steam. A 5% reduction in bagasse moisture content resulted in a US$2.40/hr reduction in the HP steam-generating cost and potential surplus bagasse revenue gain of US$280/hr. The return condensate temperatures and the bagasse moisture content showed the largest influence on the efficiencies of the deaerator and boiler, respectively. The bagasse moisture content had the largest influence on the steam-generating cost, followed by flue gas temperature, excess air, return condensates temperature, and lastly, the percentage of cold water used as feedwater.

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5.1. Introduction

Growing awareness of depleting fossil fuels and the corresponding increases in energy prices has prompted renewed interest amongst industry stakeholders and policymakers to improve energy usage through the establishment of energy-efficiency oriented policies [1]. One aspect of this renewed interest is the growing research focus on the definition of suitable energy indicators for tracking the benchmark of energy-intensive processes [2–5]. The growing proliferation of the development of energy indicators has led to conceptual questions relating to what to measure, how to define energy indicators, and how to link these energy indicators in evaluating the energy performance of an organization [2,3]. Energy indicators are often defined as the ratio of the output of useful energy (or product) to the total energy input [4,5]. Despite the usefulness of such energy indicators for managerial level energy reporting or benchmarking, recent studies have argued that they provide inadequate detail for plant personnel to detect and correct the process activities responsible for energy wastage through improved control systems [6–8]. In this regard, several studies are now focused on understanding the relationships between energy performance measures by developing causal models and encouraging industries to calculate energy indicators as correlations of the process activities with the largest effect on energy usage [3,5,8].

For the sugarcane industry, energy improvement can position the industry to improve its economic viability through the additional revenue stream from the valorization of bagasse [9]. Bagasse is the resultant fibrous residue after sucrose extraction and is used as fuel in the boiler to produce steam for sustaining the electrical and process heat demands of the sugarcane mill operations [10]. In the past, there was no justifiable use for bagasse hence to avoid the costs related to excess bagasse disposal, the boilers in the sugarcane factories were inefficiently operated and designed [9,11]. However, the growing emphasis on increasing energy demands coupled with reducing fossil resources has made bagasse to be recognized as a key feedstock in the growth of the biofuels and bioproducts industries. As such, the fact that surplus bagasse generation is the sinew of economic growth for the sugarcane industry, energy efficiency improvement has become of paramount importance [8,11,12]. The boiler is reported to be responsible for 30 to 40% of the bagasse energy wastage in the sugarcane mill [13]. While from an exergy perspective it was observed to constitute 96% of irreversibility in the cogeneration system [14]. In this regard, the improvement of the boiler operations and design is crucial for the economic growth of the sugarcane mills to be possible through bagasse valorization.

The energy indicator for measuring the energy conversion efficiency of the boiler unit in a sugarcane mill is commonly defined as a ratio of the heat transferred to the generated steam to the bagasse heat input [15,16]. This energy indicator is useful as a performance measure for the boiler unit, however, it provides limited information for identifying the process variables responsible for energy wastage in a manner that corrective actions based on advanced control strategies can be implemented.

Therefore, this study aims to identify the boiler unit variables whose steady-state deviations lead to inefficiencies and to define energy indicators for energy targeting based on the identified variables. This projection of the variable effects on the defined energy indicators is considered important for identifying the controlled variables (CVs) requiring precise monitoring and control. The Aspen Plus® cogeneration simulation of a typical sugar mill that processes 250 tonnes of cane/hr is used in this work to conduct the sensitivity analysis of the defined energy indicators to the variations in the boiler variables [17]. The rest of the paper is organized as follows: Firstly, a description of the typical boiler unit and the operational problems encountered during their operation in sugarcane mills is discussed. This is done to identify the process variables which govern the operation of the boiler unit. Secondly, energy and economic indicators considered suitable for measuring the performance of the boiler are defined. This is followed by a discussion on the findings from the sensitivity analysis.

5.2. Methods

5.2.1. Boiler system

The goal of any boiler system is to convert water to steam in a cost and energy effective manner. Figure 5-1 is a schematic diagram of the boiler system, which shows its main components the boiler unit, returned condensate tank, and the deaerator system as well as the sugar production units responsible for water (evaporator unit) and bagasse supply (extraction unit).

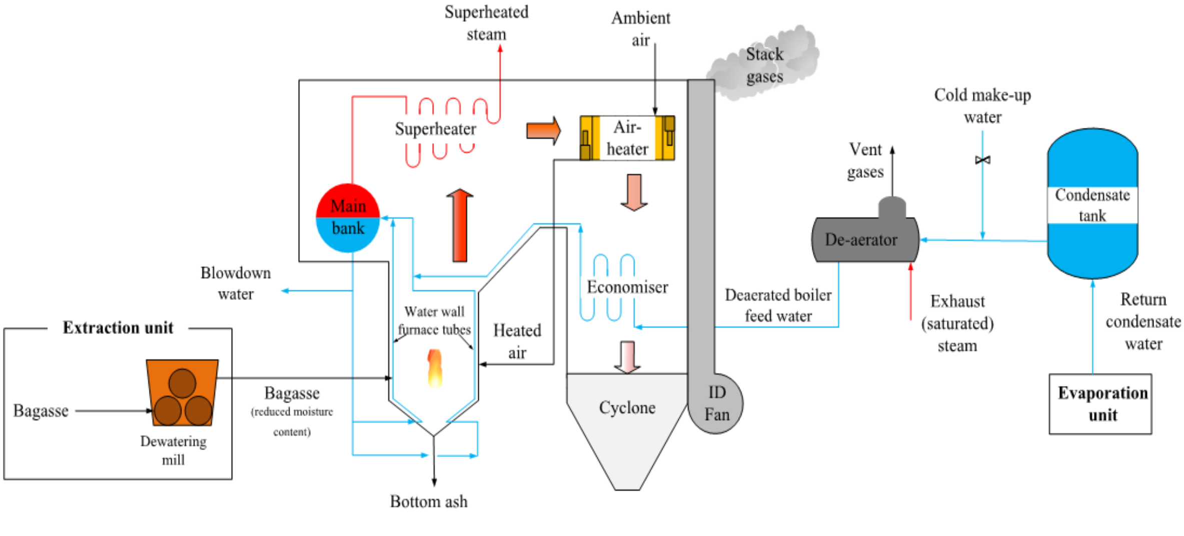

Figure 5-1:Typical process flow diagram of the boiler system in the sugarcane factory

5.2.1.1. Bagasse supply from the extraction unit

In the extraction unit, a diffuser is used to extract sucrose from the shredded sugarcane. Water commonly termed imbibition water is added to the diffuser to facilitate sucrose extraction. The remaining fiber after sucrose extraction is termed bagasse [18]. Bagasse is dewatered in the dewatering mills to reduce its moisture content to around 50% and increase its value as fuel in the boiler unit [18]. The calorific value of a fuel is a measure of the total energy released as heat when fuel is completely combusted using oxygen under standard conditions. As shown in Equation (5-1) and (5-2) [19], the gross and net calorific values of bagasse rely on the bagasse moisture, ash, and dissolved solids (DS) content. Of these three variables, the bagasse moisture component has the largest coefficients in both the GCV and NCV. Therefore, any inefficiencies in the dewatering mill will affect the achievable calorific value of bagasse, thereby reducing the overall efficiency of the boiler operations. The NCV equation is based on a bagasse temperature of 20°C and hydrogen content of 5,91% on a dry basis [19].

$$\mathrm{GCV} = (19605 - 196.05\mathrm{M} - 196.05\mathrm{A} - 31.14\mathrm{B}) \qquad (5\text{-}1)$$

$$\mathrm{NCV} = [18260 - 207.01\mathrm{M} - 182.06\mathrm{A} - 31.14\mathrm{B}] \qquad (5\text{-}2)$$

GCV = Gross calorific value of the boiler fuel, kJ/kg

NCV = Net (lower) calorific value in kJ/ kg

M = Moisture % wet bagasse

A = Ash % wet bagasse

B = Dissolved solids % bagasse

The increase in the ash (sand) content of bagasse results in lower bagasse calorific values and a significant increase in tube erosion [20]. The high ash content of the bagasse is commonly a result of cane harvesting during, or immediately after, a rainfall event, which increases the soil load in the sugarcane entering the mill [18]. Moreover, if the dissolved solids (DS) content of the bagasse is high, the ash content of the bagasse will have a higher content of alkali metals [21]. Alkali metal salts condense onto the convection heating surfaces thereby hindering the transmittance of heat in the boiler. Inadequate shredding of sugarcane, the amount of imbibition water used, and the overall settings of the diffuser will influence the amounts of dissolved solids lost in the bagasse stream [22,23].

5.2.1.2. The boiler unit

The typical modern boilers in the sugarcane industry generate steam at a pressure of 3 100 kPa and a temperature of 390˚C [24]. Bagasse is incinerated in the boiler unit to generate superheated steam. Because of the high pressure of this steam relative to other streams in the sugarcane factory, the superheated steam is referred to as high-pressure (HP) steam. The water-tube boiler is widely utilized in the sugar industry. Fuel is incinerated in the furnace chamber, (Figure 5-1), creating hot combustion gases, which heat the water for steam generation. The ambient air used for combustion and the boiler feedwater from the deaerator is heated in the air preheater and economizer, respectively using the flue gas heat. The air-heater is normally situated before the economizer [20]. For the steady-state Aspen Plus® simulation of the cogeneration plant, the flue gas exits the boiler at a temperature of 190°C, and 25% air in excess of the stoichiometric air required for complete combustion is used [14]. A high flue gas temperature represents a wastage of energy that could have been potentially used in the system. The final flue gas temperature exiting the boiler stack must not drop below its acid dew point to minimize corrosion of the metal surfaces in the boiler system.

Before being discharged to the atmosphere, the particulate matter in the flue gas is removed using the scrubber system. The induced draft (ID) fan is used to drive out the flue gases through the stack to the atmosphere. To avoid erosion related problems, wet ID fans (downstream of the scrubber) are preferred to dry ID fans (upstream of the scrubber) [20]. Also, wet fans absorb less power because of the cooler and denser gas handled [20]. The burner system needs to be capable of maintaining the required air to fuel mixture ratio throughout the firing process without continuous adjustments [25]. If the control technology used is unable to precisely hold the air to fuel ratio at the desired set-point, it prompts the need for increased excess air usage to compensate for the inconsistencies in the burner performance [25]. This increased usage of air represents a portion of the bagasse energy content (combustion heat) that must be directed for the heating of air, thereby resulting in a loss of potential revenue through surplus bagasse export. The efficiency of the boiler is calculated as:

$$\text{Boiler efficiency}, \eta_B = \frac{(\dot{m}_{st} * h_{HP}) - (\dot{m}_{BFW} * h_{BFW})}{\dot{m}_{bagasse}\ GCV} = \frac{\text{Heat in steam generated}}{\text{Heat in fuel input}} \qquad (5\text{-}3)$$

Where,

$\dot{m}_{st}$ = Quantity of steam generated, kg/hr

h_{HP} = Total specific enthalpy of the generated steam, kJ/kg

$\dot{m}_{BFW}$ = Quantity of boiler feedwater, kg/hr

h_{BFW} = Specific enthalpy of feedwater to the boiler, kJ/kg

$\dot{m}_{bagasse}$ = Quantity of bagasse used as fuel, kg/hr

5.2.1.3. Feedwater supply from the evaporator unit

The raw sugar factory returns about 85 % of the steam generated as condensate; condensate that in the ordinary course of events should be uncontaminated [18]. The return condensate is mainly taken from the evaporator unit with a small portion coming from the air heater in the sugar drying unit [24]. In the evaporator unit, the first effect condensate is returned to the boiler system; however, sometimes the second effect condensate can be used to supplement the feedwater supply [18]. Inadequate control of the juice level in the evaporator unit can lead to juice filling up the vessel and flowing through to the condensate system [26]. This results in sugar contamination of the return condensate being directed to the boiler system. Sugar contamination of feedwater leads to financial loss due to the costs associated with boiler downtime, repair, and maintenance [26]. The steady-state temperature of the returned condensate in the condensate tank is assumed to be 90 °C in the Aspen Plus® model [17].

5.2.1.4. The deaerator

The feedwater supply is an essential part of the boiler system. The deaerator is responsible for ensuring the return condensates are conditioned to the specified temperature, flow, and quality before being used as boiler feedwater. The deaerator uses low-pressure steam to heat the water to the saturation temperature corresponding to the steam pressure in the deaerator, thereby scrubbing out and carrying away oxygen and other dissolved gases [18]. The steam provided to the deaerator offers the physical oxygen stripping action, while simultaneously heating the return condensate and cold makeup water to the saturation temperature [27]. Though most of the steam used in the deaerator condenses, approximately 5 to 14% of the steam is vented out to accommodate the stripping requirements [27]. The exhausted, low-pressure steam from the turbines is used in the deaerator and the amount used depends on the return condensates temperature and flow.

If the return condensate temperature is low, then more heating steam is required to raise the temperature of the water to the steam saturation temperature. On the other hand, if the return condensate flow is low, increased amounts of cold water are required to meet the boiler feedwater flow requirements. This leads to more steam being required to raise the temperature of the cold water. The rate of the vent gases is a function of the deaerator type, size, and the amount of cold water added. In addition to heating steam requirements, the vent rate and the corresponding heat losses are high when there is pronounced usage of cold, oxygen-rich water [27].

5.2.2. Energy indicator definition

5.2.2.1. Boiler unit predictive energy indicator

The boiler is responsible for over 30% of the wastage of the bagasse energy through heat losses [13]. Figure 5-2 is a schematic diagram of the mass and energy flows in a boiler unit [28]. The boiler heat losses are also illustrated in Figure 5-2 and these include:

i. L1-Loss due to dry flue gas
ii. L2-Loss due to water formed by combustion of the hydrogen in the bagasse
iii. L3-Loss due to bagasse moisture
iv. L4-Loss due to carbon monoxide loss
v. L5-loss due to surface radiation and convection
vi. L6-Loss due to incomplete carbon combustion

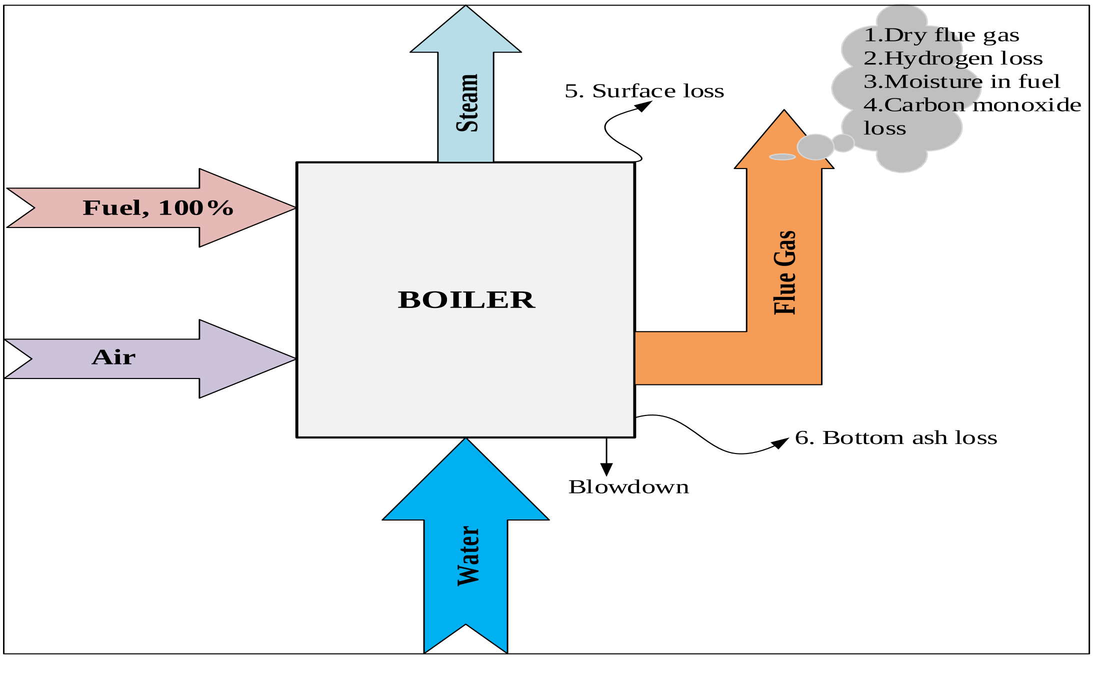

Figure 5-2: An example of the boiler system heat losses

Source: [28]

The boiler efficiency formula defined in Equation (5-3) only looks at the ratio of the heat transferred for steam generation to the energy input in bagasse and hence lacks relevant data for identifying, quantifying, and correcting the areas of energy wastage in a boiler system. For these reasons, it is considered essential to have an energy indicator that can be decomposed to identify the different contributions of the process variables in a manner that allows for strategized causal analysis, correction of the influential process variables through the implementation of appropriate automated control systems. The flue gas losses are the major heat losses in the boiler system, contributing to approximately 4 to13 % of the heat losses [18]. The increase in bagasse moisture and excess air amounts used results in the diversion of some of the bagasse energy for evaporating the water in the bagasse and air streams. On the other hand, if the flue gas is not recovered for use in waste recovery systems [29], a high flue gas temperature indicates useful heat that could have been recovered in the boiler. In addition to allowing for improved energy monitoring and control, such an indicator can help to identify possible waste heat recovery projects for implementation [17].

The main constituents of the flue gas are nitrogen, oxygen, water, and carbon dioxide. Water and carbon dioxide are the products of the combustion reaction process. The relatively inert nitrogen gas constituting the flue gas composition is brought into the boiler system with the combustion air. As the flue gases exit the boiler system, they inevitably absorb combustion heat thereby reducing the heat recovery efficiency. The sensible heat loss from the boiler system to the atmosphere through the flue gases represents a portion of combustion heat that was not transferred to the water for steam generation. The expression $\int_0^T m * C * \ dT$ was used to obtain the sensible heat loss contributed by each component gas in the flue gas [30]. Since the specific heat capacity is a function of temperature, the expression was integrated between 0˚C and the flue gas temperature denoted as "T". The sensible heat carried by each flue gas per kilogram (kg) of bagasse burnt is shown in Table 5-1.

Table 5-1: Sensible heat carried by each gaseous product of combustion

Gaseous Products of Combustion	**Sensible Heat loss**
Nitrogen, N_2	$q_1 = [4.43(1-w) * m] * 1.05T$
Oxygen, O_2	$q_2 = [1.33(1-w) * (m-1)] * 0.91T$
Water , H_2O	$q_3 = [0.585(1-w) + w] * 2.09T$
Carbon dioxide, CO_2	$q_4 = [1.72(1-w)] * 0.90T$

Based on the summation and simplification of the expressions in Table 5-1, the total sensible heat loss from the boiler unit is given as [30]:

$$Q = [(1-w)(1.4m - 0.13) + 0.5] * 4.184T \quad (5\text{-}4)$$

Where,

Q = total sensible heat loss in flue gases, kJ/kg

w = moisture content per unit bagasse

m = ratio of actual mass of air used for combustion to the theoretically required mass

T = temperature of the flue gases, in ˚C

Contrary to the GCV, the NCV formula assumes that the water formed by combustion as well as the water in the fuel remains in the vapor state [20]. Inarguably, the GCV is a good measure of the theoretically available heat in fuel [20]. However, in industrial practice, it has not yet been considered technically and economically justifiable to reduce the combustion product's temperature below the dew point [31]. Therefore, the NCV gives a more accurate indication of the actual heat practically obtainable. In this context, the NCV formula in Equation (5-2) already takes into account the L2 and L3 losses and will thus be used to reflect on these boiler heat losses. The combined unburnt carbon losses (L4 and L6) are assumed to have a heat loss equivalent to 1.5% of the GCV of bagasse [30]. Therefore, the remaining quantity of heat transferred to the steam per unit mass of bagasse is [30]:

$$\mathrm{M_v} = (\mathrm{NCV} - \mathrm{Q}) * \alpha\gamma \tag{5-5}$$

Where,

$\mathrm{M_v}$	=Heat transferred to the generated steam per kg of combusted bagasse, in kJ/kg
NCV	= Net calorific value in kJ/ kg
Q	= Total sensible heat lost in flue gases, in kJ/kg
α	= (1-0.015), the coefficient for the unburnt carbon heat losses L4 and L6.
γ	= (1-0.015), the coefficient for heat losses due to L5.

Equation (5-5) represents the available fuel heat content for steam generation after the consideration of the heat losses in a boiler unit. Therefore, the overall boiler efficiency is defined as the ratio between the practically available fuel heat content for steam generation and the theoretically available fuel heat content:

$$\text{Overall boiler efficiency}, \eta = \frac{\mathrm{M_v}}{\mathrm{GCV}} = \frac{\text{Heat transferred to the steam}}{\text{GCV of the bagasse}} \tag{5-6}$$

Steam generated in the boiler is a compressible fluid whose density changes with temperature and pressure variations. Therefore, due to the nature of steam combined with the available measurement technologies and complex pipe connections, there are limitations in obtaining reliable steam flow readings [5,32]. Damms [33] also reported on the constraints to the energy management program imposed by the unreliable flow measurements of steam. Furthermore, insufficient instrumentation and imprecise sensors due to cost and technical constraints are reported as some of the problems encountered in the adequate control and process monitoring of the boiler unit [5,22,23]. A comparison of the required measurements for determining the boiler efficiency based on Equation (5-3) and Equation (5-6) are given in Table 5-2. Only 6 variable measurements are required for the predictive boiler efficiency which considers the heat losses. For the boiler efficiency based on Equation (5-3), 10 variable measurements are required. In addition to the reduction in the number of measurements required, the proposed boiler efficiency also eliminates the need for steam and bagasse flow rates, thereby reducing the imprecise estimation of the boiler performance while providing a tool that can be used to identify areas for energy saving.

Table 5-2: Comparison of the required measurements for estimating the efficiency of the boiler based on the defined methods

Boiler efficiency Equation (5-3)	**Predictive boiler efficiency** Equation (5-6)
Feedwater flow rate	Bagasse moisture, ash, and DS content
Feedwater temperature and pressure	Flue gas temperature
High-pressure steam flowrate	Flue gas oxygen concentration
High-pressure steam temperature and pressure	Oxygen flow rate
Bagasse flowrate	
Bagasse moisture, ash, and DS content	

5.2.2.2. Deaerator energy indicator

Low-pressure steam is used in the deaerator to heat both the return condensate and the cold makeup water to its saturation temperature plus the amount vented with the incondensable gases. To quantify the performance of a deaerator, the defined energy indicator is defined as the amount of steam used per tonne of boiler feedwater exiting the deaerator:

$$\text{Deaerator energy indicator (kg/tonne)} = \frac{\dot{m}_{\text{Steam consumed}}}{\dot{m}_{\text{Boiler feedwater}}} \qquad (5\text{-}7)$$

For the same inlet water proportions and temperature conditions, the value for the defined energy indicator must remain constant. Although not shown in the present study, any deviation in the value of this indicator for the same inlet water conditions would be an indication of the deaerator operational problems and not the feedwater supply system. This aspect of elimination of the feedwater supply system allows for a more strategized approach to troubleshooting the energy inefficiencies in the deaerator. However, for this to be possible, benchmarks for the deaerator energy indicator need to be established for different inlet water conditions.

5.2.2.3. Boiler system economic indicator definition

The steam cost is considered an important benchmark of any boiler system. Benchmarking the cost of steam generation is an effective way to assess the efficiency of the steam generation system from an economic perspective [34]. Unloaded steam cost and loaded steam cost are the terms used to distinguish between the two methods used to calculate the steam generation cost [34]. Unloaded steam cost involves an arbitrary comparison between the amount of steam produced and the cost of fuel required to produce steam. It is a simplified method for steam cost calculation and is dependent upon the fuel type, fuel cost, boiler efficiency, feedwater temperature, and steam pressure [34]. On the contrary, loaded steam cost captures all aspects and costs of producing steam, which provides a more accurate steam cost. In addition to the variables used in the unloaded steam cost computations, the loaded steam cost also includes factors like the power consumption of all auxiliary machinery used in the boiler, chemical costs, water and sewer, emissions payments, labor costs, maintenance, and waste disposal costs [35].

While acknowledging that the loaded steam cost method is more accurate and inclusive, the unloaded steam cost method is used in this study as it is easy to compute and provides a reliable indication of the contributory effects associated with the operation of the boiler. The boiler and deaerator are the main components making up the steam generation system. Therefore, it follows that the economic monitoring of the steam generation system should be done so with consideration of both the deaerator and the boiler unit. In this regard, the steam generation cost formula in this study is modified from the literature formula [34] to account for the operation of the deaerator based on the temperature and flow of the return condensates and the cold make up water. Furthermore, to account for the influence of the boiler losses in the economics of steam generation, the boiler efficiency defined in Equation (5-6) is used in the computation of the steam-generating cost. Therefore, the present study modified steam-generating cost indicator is given as:

$$S_C = \frac{1000a_F(h_{HP} - (\%\ \text{makeup} * h_{mf} + \%\ \text{condensate} * h_{cf}))}{\eta} \tag{5-8}$$

S_C = Steam cost unloaded in US$/tonne of HP steam

a_F = Fuel cost in US$/kJ bagasse

h_{HP} = Enthalpy of high-pressure steam in kJ/kg.

η = Boiler efficiency

h_{mf} = Enthalpy of cold make-up water in kJ/kg

h_{cf} = Enthalpy of return condensates in kJ/kg.

5.2.3. Sensitivity studies

Studies by Munir et al. [16] investigated the effect of ambient air temperature and the flue gas temperature and oxygen concentration on the boiler efficiency calculated based on total steam heat value. A 22˚C decrease in flue gas temperature resulted in a 1% increase in boiler efficiency and two kg of steam were produced per kg of bagasse with a moisture content of 46% [16]. Sensitivity analysis is a series of test runs in which purposeful changes are made to the input variables of a process model, such that the changes in the output response are observable. In this study, the sensitivity analysis of the defined boiler (Equation (5-6)), deaerator (Equation (5-7)), and overall steam-generating unit energy indicators (Equation (5-8)) under the steady-state variations of the process variables is done. For the boiler energy indicator, the considered variables are bagasse moisture, flue gas temperature, and oxygen concentration. The temperature and flow rates of the cold water and the return condensates streams are used for the evaluation of the deaerator. The Aspen Plus® cogeneration system developed by Dogbe et al. [17] for a typical sugarcane factory that processes 250 tonnes/hr of sugarcane was used to conduct the sensitivity analysis. The steady-state values used in the Aspen Plus® cogeneration system are presented in Table 5-3 together with the variables selected for the sensitivity studies and their considered value variations. For each model-based sensitivity run, one variable is varied while the rest are held constant at their steady-state value. A bagasse price of US$35.36/tonne is used [36].

Table 5-3: Steady-state variables and values used for the sensitivity studies in the Aspen Plus® model

Variables	**Value**	**Units**
Steady-state assumptions for sensitivity analysis		
Excess air	25	%
Flue gas temperature	190	˚C
Bagasse moisture content	50	%
Bagasse ash content	1.85	%
Bagasse DS content	3.69	%
HP steam flowrate (at 390 ˚C and 31 bar)	112 498.80	kg/h
Boiler feedwater flowrate	115 875.02	kg/h
Bagasse flow rate	50 597.27	kg/h
% of cold water used	10%	Coldwater % total water to deaerator
Return condensate temperature	90	˚C
Variables considered for the sensitivity studies		
Bagasse moisture	45; 50; 55	% bagasse moisture content
Flue gas temperature	180.5; 190; 199.5	˚C
% excess air	23 - 30	% oxygen content in flue gas
% of cold water used	2 - 20	Coldwater % total water to deaerator
Return condensate temperature	80 - 100	˚C

5.3. Results analysis and discussion

5.3.1. Boiler unit sensitivity analysis

5.3.1.1. Effect of bagasse moisture content

The moisture entering the boiler with bagasse leaves as superheated vapor. The higher the bagasse moisture content, the greater the amount of water vapor formed during the combustion process in the boiler unit. Thus, combustion heat that would have been otherwise used in the production of HP steam is now diverted to heating the moisture in bagasse to produce superheated vapor, which leaves the boiler with the flue gas stream. This notion is shown in Table 5-4 as the heat transferred for steam generation drops by 14.8% for a 5% increase in bagasse moisture content. This heat loss is mainly due to the sensible heat required to bring the bagasse moisture to the boiling point, the latent heat of evaporation of the moisture, and the superheat to bring this steam to the temperature of the flue gas. Therefore, in addition to the reduction of the moisture content, further heat loss reductions can be realized by lowering the temperature of the flue gas such that the superheat required to bring the formed water vapor to the flue gas temperatures is reduced. The potential bagasse revenue gain in Table 5-4 is calculated based on the baseline bagasse revenue when using bagasse with a moisture content of 50%.

Table 5-4: Boiler heat balances with bagasse moisture variations

Variables	Bagasse moisture		
	45%	50%	55%
GCV (kJ/kg bagasse)	10323.00	9364.20	8401.90
NCV (kJ/kg bagasse)	8484.60	7471.20	6454.10
Heat transferred to the steam (kJ/kg bagasse)	6184.10	5388.70	4590.30
Boiler efficiency (%)	69.91	67.55	64.63
kg HP steam/kg bagasse	2.60	2.27	1.93
Potential bagasse revenue gain (US$/hr)	280.19	0	-378.95

When the other operating variables of the boiler are maintained constant, a reduction in bagasse moisture content from 50 to 45% results in a 2.36% and 9.29% increase in boiler efficiency and GCV, respectively. The study results correspond with the findings by Magasiner et al. [37], which also indicated a 2 to 3% boiler efficiency fluctuation for every 5% change in the bagasse moisture content. The dewatering mill in the extraction unit is the process equipment responsible for increasing the value of bagasse as a fuel in the boiler house, by decreasing its moisture content. The increase in the net calorific value of bagasse when the bagasse moisture content is reduced to 45%, results in a 15% increase in HP steam produced per kg of bagasse and US$280/hr potential surplus bagasse revenue gain. However, the bagasse savings must be further evaluated by considering the additional energy requirements in the dewatering mill to enable further bagasse moisture content reductions.

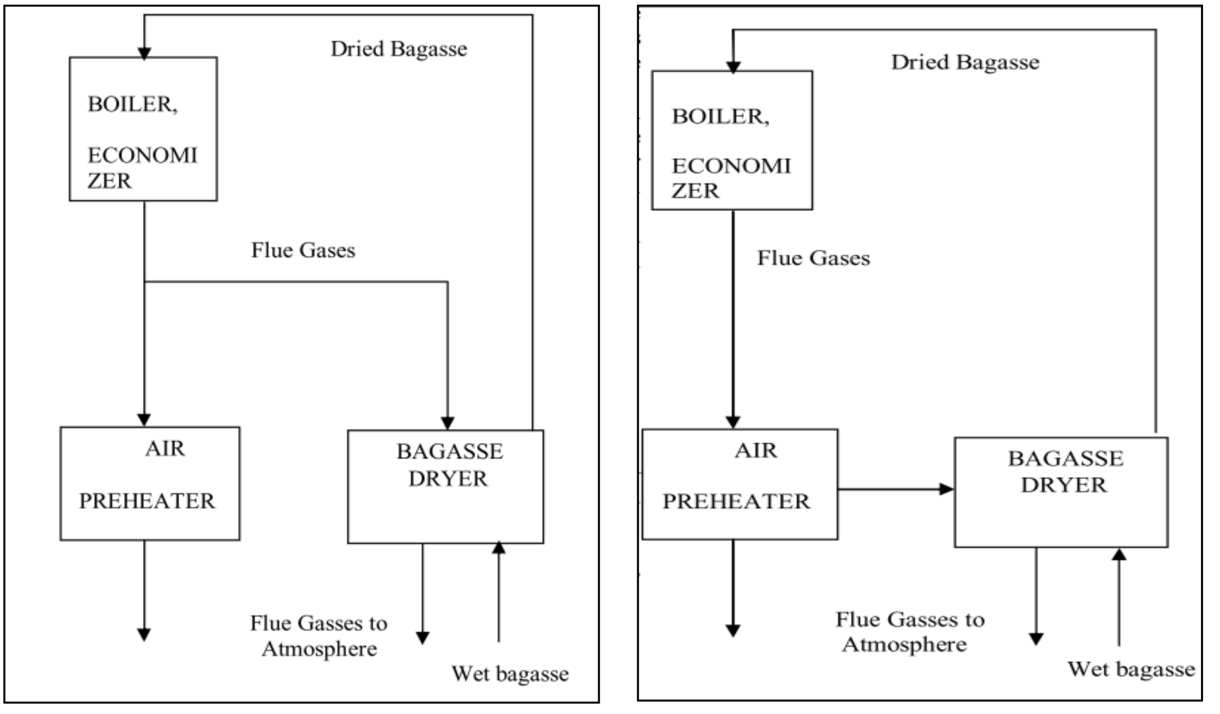

Figure 5-3: Different arrangements for bagasse dryer using flue gases

Source: [38]

Previous have also suggested the use of both the dewatering mills and bagasse dryer to attain lower bagasse moisture contents [38]. Figure 5-3 is a schematic diagram of a typical arrangement of the literature proposed bagasse dryer arrangements using flue gases. For the first bagasse dryer arrangement, the flue gas stream is split between the air preheater and the dryer and for the second arrangement in Figure 5-3, the flue gas is first used in the air preheater and a portion of flue gas exiting the heater is then directed to the dryer. The choice of an arrangement to use will depend on the required heating and drying requirements of air and bagasse, respectively. Bagasse moisture reductions of up to 45% have been reported to have been attained with a bagasse dryer using flue gases for drying purposes [38]. Hence the installation of a bagasse dryer can be an effective way of reducing both the bagasse moisture content and the flue gas heat content. However, care must be taken when operating the bagasse dryer as bagasse is highly self-ignitable at such low moisture contents [18].

5.3.1.2. Effect of flue gas temperature

Table 5-5 shows the effect of varying flue gas temperature on the operation of the boiler unit. The flue gas temperature is an indication of how effectively combustion heat is transferred to the boiler water for the generation of steam [37]. At 5% lower flue gas temperature, the heat transferred to steam and the boiler efficiency are shown to increase by 44 kJ/kg bagasse and 0.46 %, respectively. This increase in boiler efficiency corresponds to the observations by Munir et al. [16] that there is a 1%

increase in the boiler efficiency for every 20˚C reduction in flue gas temperature. A 5% decrease in the flue gas temperature is shown to result in only US$17.50/hr potential surplus bagasse revenue increase as compared to the value of US$280/hr observed for a 5% decrease in bagasse moisture content. Hence while the reduction of flue gas temperature is essential, the economic gain from a 5% bagasse moisture reduction is higher.

Table 5-5: Boiler heat balances with variations in the flue gas temperature

Variables	Flue gas temperature		
	180.50	**190.00**	**199.50**
Heat transferred to the steam (kJ/kg bagasse)	5432.40	5388.70	5345.10
Boiler efficiency (%)	68.01	67.55	67.08
kg steam/kg bagasse	2.28	2.27	2.25
Potential bagasse revenue (US$/hr)	17.50	0	-17.78

An increase in the flue gas temperature can be consequential to the deterioration of the boiler heat transfer equipment (soot or scale build-up) or operational errors like damper settings in the induced draft (ID) fan [18]. For adequate combustion, temperature, time, and turbulence are required [18]. If the furnace pressure goes further into the negative zone, it means the ID fan is taking combustion gases too quickly from the furnace through to the stack [20]. This means there are limited time and turbulence provided for complete combustion to take place and for the combustion gases to transfer their heat to the boiler feedwater. The furnace pressure transmitter must give the readings frequently so that the operator can reduce the ID fan speed or adjust the damper settings from looking at the pressure readings [25]. Continuous monitoring of furnace pressure needs to be carried out and to avoid frequent speed adjustments, set-point optimization can be a solution to find robust optimal speed set-points for use during different boiler operating conditions. Wienese [20] advocates for flue gas temperatures below 200˚C the ash fusion temperature.

However, in the aim of reducing the flue gas temperature care must be taken not to allow the temperature to drop below the practical limit beyond which corrosion will be worsened at the tail end of the heating surface. Sulphuric acid is the main acid responsible for corrosion in the bagasse fuelled boilers [22]. The active point of sulphuric acid is dependent on the partial pressures of water vapor, sulfur trioxide, and hydrogen chloride in the flue gas [22]. The sulfur in the bagasse oxidizes to sulfur dioxide during the combustion process and can further oxidize to sulfur trioxide at estimated conversion rates of 1 to 3% [22]. The acid dew point is normally less than 90˚C [7]. Low-temperature corrosion takes place when the metal surface temperature drops below the acid dew point [18]. These metal surfaces consist of the economizer, air heater, flue gas ducting, and scrubber. Therefore, to avoid metal corrosion, the flue gas temperatures must be above 90˚C while also not exceeding temperatures over 200˚C to prevent ash fusion.

5.3.1.3. Effect of excess air

The operational goal of the boiler unit is to produce steam at the lowest energy wastage, as is possible. Excess air is heated up using the combustion process energy. Therefore, above-specified ranges, excess air represents potential energy that is not transferred to the water in the boiler [20]. The acceptable oxygen levels are between 4 to 6% on a dry volume basis for bagasse fuelled boilers [6]. Literature values from a bagasse fuelled boiler indicate a 0.5% increase in boiler efficiency when the excess air is reduced by 10% [21]. This value corresponds to the present study results in Figure 5-4, which show a 0.25 % increase in boiler efficiency when excess air used is reduced from 30 to 25%. While the changes in the flue gas temperature and oxygen concentration have a small effect on the boiler efficiency, it is considered essential to solve these minute energy losses in the boiler operation as the number of them left unattended can accumulate to even bigger energy losses.

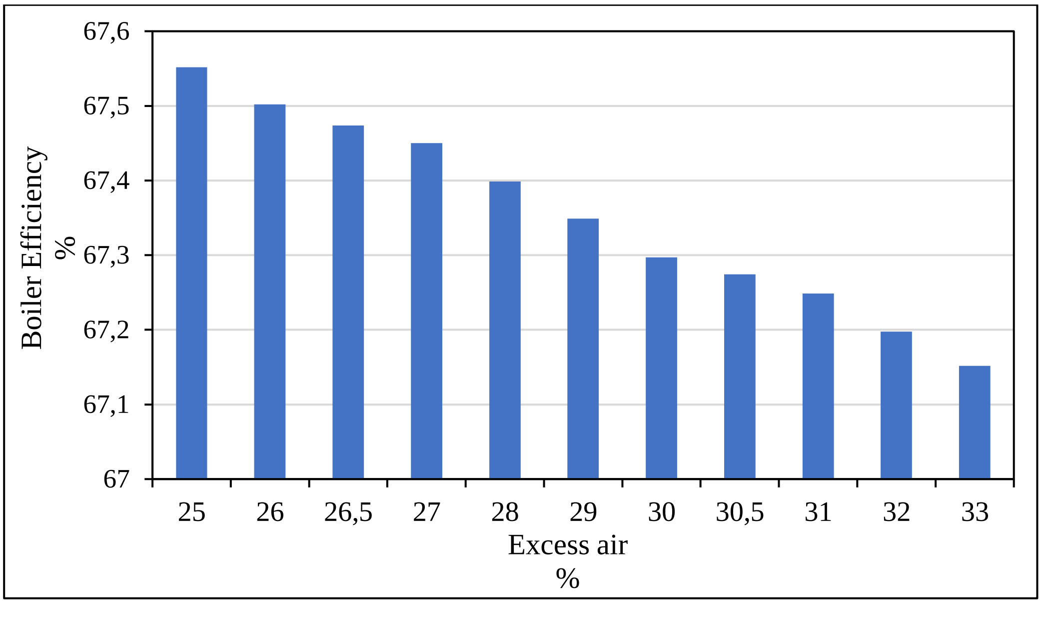

Figure 5-4: Boiler efficiency variation with the percentage of excess air

Since the boiler operates on negative pressure, air from the atmosphere can be sucked into the boiler through any holes in the ducting or seals. Such a scenario leads to high airflow rates in the system and increased heat losses in the boiler unit as the moisture in the sucked air, is heated from ambient temperature conditions to the flue gas temperatures before exiting with the flue gas as superheated vapor. Hence, the present study recommends the frequent carrying out of the boiler heat balances combined with the use of accurate sensors for combustion airflow, and the flue gas temperature and oxygen content. This can enable strategized causal analysis and early identification of areas permitting the sucking of atmospheric air into the boiler system.

A repeatable air to fuel ratio control is essential for the efficient operation of the boiler and this relies on the ability of the burner system to provide the air to fuel mixture in the required proportions [18]. Failure to hold precise air to fuel ratios prompts the need for increased excess air rates to compensate for the inconsistencies in the burner performance [25]. The commonly used method for burner control is the use of a single actuator to simultaneously drive both the fuel valve and combustion air damper. For systems involving complex pipe linkages with multiple pivots, maintaining a precise air to fuel ratio throughout the firing rate can be challenging [25]. However, with the recent advances in digital control technology, the new burner control systems use two actuators to independently control fuel and combustion air [25]. When these systems are coupled with the advanced programmable control technology, they can allow for precise air to fuel ratio control, automatic fuel changeover, combustion monitoring, and combustion optimization based on the adjustment of the flue gas oxygen concentration [25]. Therefore, instead of replacing the boiler the installation of separate actuators and advanced control equipment can be an alternative strategy for enabling a factory to reduce the losses in bagasse energy in the boiler, thereby resulting in increased surplus bagasse availability. However, for such decisions to be systematically made the cost associated with procuring either a new higher-pressure boiler or new monitoring and control systems must be weighed against their expected economic benefits to the factory.

Intricate, multiple, and parallel pipe connections have been reported to exist in some sugarcane, hence for a factory with imprecise air to fuel ratio control, the use of the new control system with two actuators can assist to improve boiler control and ensure optimal usage of bagasse [5]. Such investments need to be evaluated in conjunction with the expected revenue gain. The price for instrumentation increases with the number of required measurements and the precision of the used sensors. Cao et al. [39] provide a structure for selecting manipulated variables with a satisfactory disturbance rejection. This approach can be extended for the evaluation of different actuators with different measurement errors to find the optimal actuator investments. Optimality can be defined for minimization of the cost of instrumentation, and the financial loss due to the effect of the measurement error and the inability of the manipulated variables to adequately adjust the controlled variables as required by the control system for disturbance rejection. The two objective functions can be combined to produce a composite objective function with user-specified weighting factors for each function or tools like the Pareto front can be used to assist with such evaluations [40].

5.3.2. Deaerator sensitivity analysis

The addition of cold make up water has two downsides when considered regarding the deaerator energy consumption. Firstly, the oxygen stripping requirement is high when more cold makeup water is used because of the elevated oxygen concentration compared to the return condensate water [12]. Secondly, more heat energy is required to raise the temperature of the cold makeup water. This notion is observed in Figure 5-5, which shows the changes in the deaerator steam consumption when the percentage of cold make-up water added is reduced or increased. From the literature quoted values [41], a 10% addition of cold make-up water is considered the baseline value for the present study and this corresponds to a deaerator steam usage of 39.36 kg/tonne of boiler feedwater. This is the steam required to raise the temperature of the return condensates and cold water to the steam saturation temperature plus the vented gases. Based on the Aspen Plus® model of the cogeneration system, the vent rate is set at about 2.3% of the deaerator steam used [17]. From Figure 5-5, it is shown that for each 2% change increase in cold water added in the deaerator, there is approximately 2.2 kg increase in the deaerator steam used per tonne of boiler feedwater.

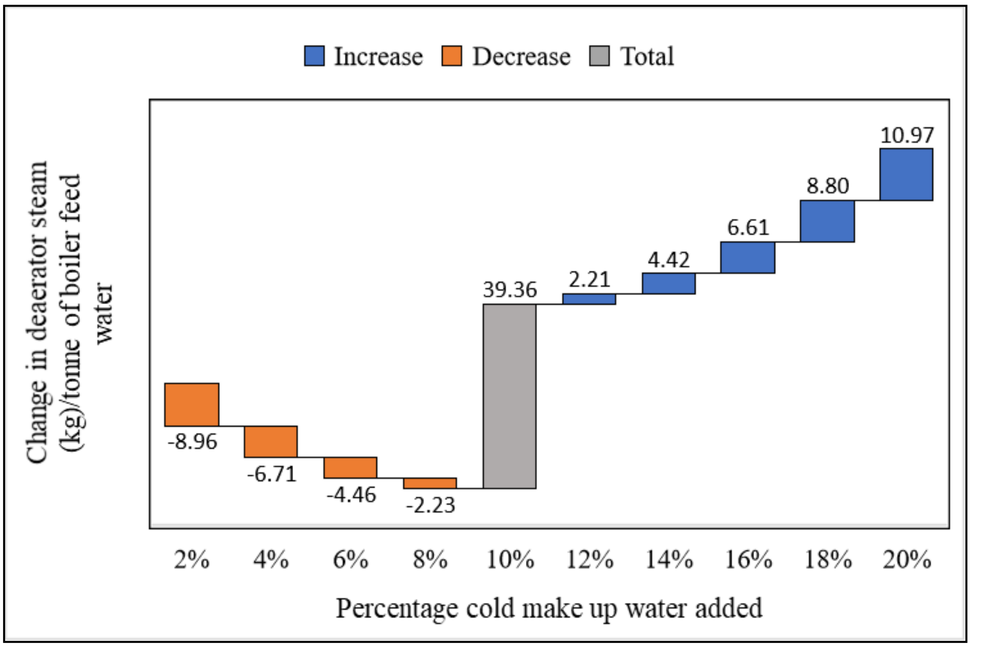

Figure 5-5: Effect of cold makeup water on the deaerator steam consumption

There is also an increase in the steam consumption of the deaerator with a decrease in the return condensate temperature due to the extra heating requirements. Based on sensitivity results which are displayed in Figure 5-6, there is a 3.1 kg increase in deaerator steam used per tonne of boiler feedwater for a 2˚C drop in the return condensate temperature. A drop in return condensates temperature from its steady-state value of 90 to 88˚C, corresponds to a 2% change in temperature. Therefore, by comparing the changes in the deaerator steam consumption (Figure 5-5 and Figure 5-6), there are more energy-saving benefits to be attained by increasing the temperature of the return condensates as compared to reducing the percentage of cold makeup water added.

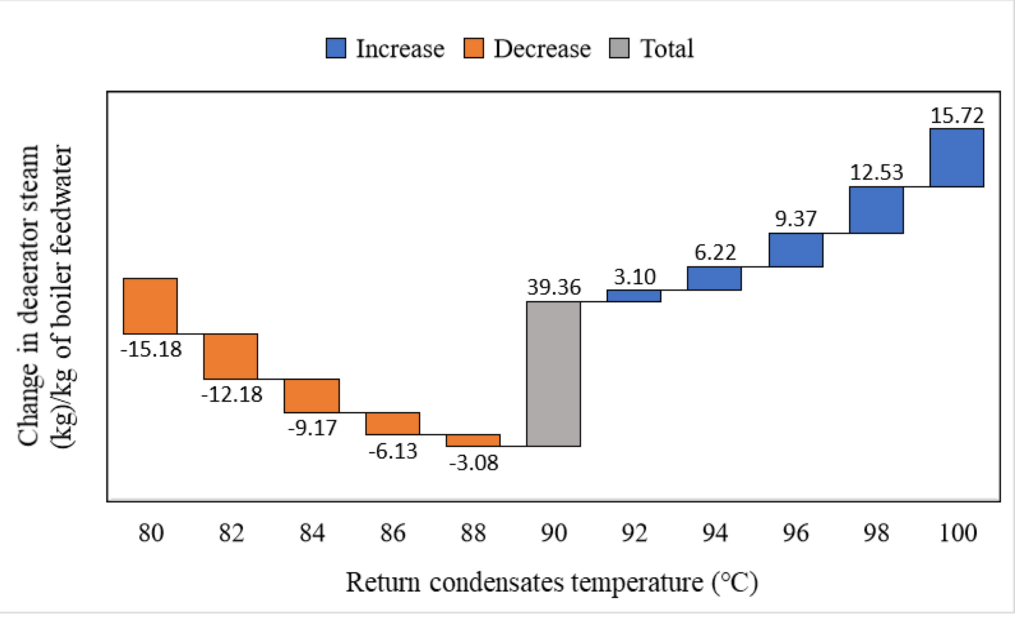

Figure 5-6: Effect of return condensates temperature on the deaerator steam consumption

Such comparisons as illustrated in Figure 5-5 and Figure 5-6 can be used to establish benchmarks for deaerator steam usage at different temperatures and flowrates of cold water and return condensates. By using such benchmarks, any deviations observed in the deaerator energy indicator value would automatically exclude the contribution of the feedwater supply system, thereby allowing for a reflection of problems that are solely due to the operation of the deaerator. For example, say the return condensate temperature is 90˚C and 10% cold make up water is added to compensate for the boiler feedwater, the benchmark based on the present study is 39.36 kg steam/tonne boiler feedwater. Therefore, any deviations observed in the energy indicator value for the same water conditions would indicate that there are issues in the operation of the deaerator, thereby allowing for more strategized troubleshooting of operational problems. Regarding the operational efficiency of the deaerator, frequent air leaks check in the piping and suction side of the pump must be done and the deaerator be well insulated [27]. Furthermore, an accurate pressure regulating valve must be used as the deaerator exhibits pressure fluctuations with sudden increases in flash steam [18].

5.3.3. HP steam-generating cost

Figure 5-7 shows the change in the steady-state HP steam-generating cost of US$18.73/hr when ±5% changes are made in the bagasse moisture content, flue gas temperature, excess air, percentage cold makeup water added, and the return condensate temperature. All temperatures are in ˚C. From Figure 5-7, the bagasse moisture content is observed to have the largest impact on the HP steam-generating cost. Flue gas temperature followed by the return condensate temperature is the next most influential variable governing the operational economics of the steam-generating unit. A 5% decrease in flue gas temperature is shown to lead to a US$0.15/hr decrease in the steam-generating cost, while a 5% increase in return condensates temperature leads to US$0.11/hr cost reductions. Therefore, for minimizing the cost of generating HP steam, the reduction of the bagasse moisture content and flue gas temperature is required, and the increase in the return condensates temperature.

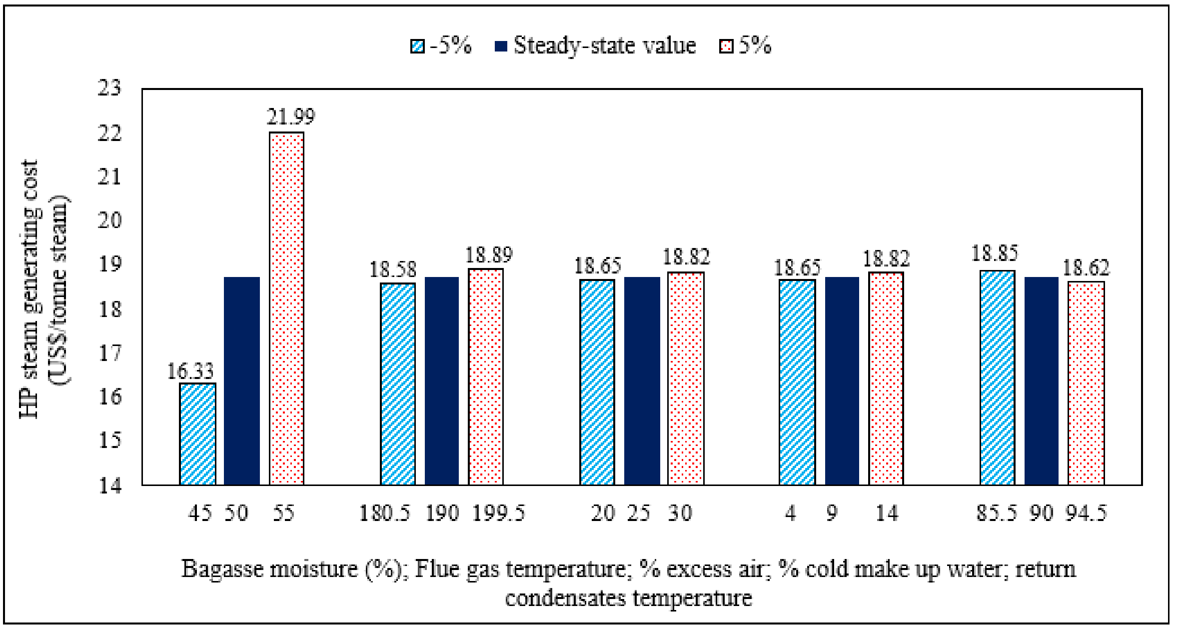

Figure 5-7: Variation in the steam-generating cost with variations in the bagasse moisture, flue gas temperature,% excess air,% cold makeup water and return condensates temperature

In literature, the steam-generating cost is calculated based on the boiler feedwater temperature and flow after the boiler. However, in the present study, the temperature and flow of the return condensate and cold water before the deaerator and not after the deaerator are considered to allow for their effect on the steam-generating cost to be quantified and evaluated. When the unmodified HP steam-generating cost formula is used, the steady-state HP steam-generating cost is US$18.16/hr which is US$0.57/hr lower than the value attained for the study modified formula. This means that 3% of the HP steam-generating cost in the modified formula is contributed by the return condensates temperature and flow conditions. Therefore, the study modified formula for HP steam-generating cost is recommended for use in sugarcane mills as it serves as a tracking device to allow for deaerator and boiler performance monitoring and improved control.

5.3.4. Strategies for reducing the HP steam-generating cost

5.3.4.1. Optimal insulation theory

Insulation can reduce energy losses by 90% and ensure proper steam pressure regulation in plant equipment [42]. Hence, the insulation of surfaces exceeding 50˚C such as the boiler surfaces, steam and condensate return piping, and fittings is often recommended [42]. Based on a given amount of insulation material, Claesson and Bengt [43] presented an optimization strategy for optimal distribution of thermal insulation such that the heat losses are minimized. Acknowledging that corner regions and other piping connections for which heat flow patterns are more complex, further pose an optimization problem, Claesson and Bengt [43] further showed how to account for such complex heat flow in the optimal distribution of thermal insulation. Some sugarcane mills have been reported to comprise multiple and parallel water and steam piping lines [5]. Hence the strategies recommended in [43] can assist in the optimal insulation of such pipes in sugarcane factories.

Ito et al. [44] applied multiple objective functions for the design of a piping system to minimize both the heat loss and the amount of insulation used while Keylon and Sahin [42] used optimal control theory to find the optimal pipe insulation thickness that minimizes the heat losses. A common approach for multiple objective functions is to sum all objective functions with appropriate weighting factors and minimize the resulting composite function [42]. Therefore, considering the effect of the return condensate temperature on energy usage and the HP steam-generating cost in a sugarcane mill, future work for optimal pipe insulation is recommended. Considering the budget constraints, optimality must be defined for minimizing the total cost associated with the cost of the insulation material, its installation, and maintenance, as well as the cost of the heat lost.

5.3.4.2. Reabsorption monitoring in the dewatering mills

Of all the variables considered in the present study, the bagasse moisture content is shown to have the largest impact on the boiler efficiency and the cost of generating HP steam. Therefore, knowledge of the bagasse moisture content is essential when evaluating the operational and economic efficiency of the boiler system. The dewatering mill in the extraction plant is the process equipment responsible for increasing the value of bagasse as a fuel in the boiler, by decreasing its moisture content; hence, the monitoring of the dewatering mill efficiency in this regard is vital. The variables that affect the operational efficiency of the dewatering mills can be classified into two groups. The first group relates to the bagasse and includes variables like the bagasse moisture before entering the dewatering mill, the sugarcane variety, and the extent of sugarcane preparation [30]. Sugarcane preparation entails the use of knives and shredders to open the sugarcane stem cells, thereby facilitating the extraction of sucrose in the diffusers [18]. From a production perspective adequate shredding of cane is required to ensure maximum sucrose extraction and minimization of sucrose losses in the bagasse stream. For the dewatering mill, good sugarcane preparation is required to allow for effective removal of bagasse water, and for the boiler, this is crucial for minimizing the reduction in the calorific value of bagasse through reduced bagasse moisture and dissolved solids (sucrose and non-sucrose) content.

The second group relates to the dewatering mill operational problems and includes fixed variables such as the geometry of the mill, the number of rolls, and the type of feeding device, and the varying variables such as mill settings, mill speed, roll roughness, mill lift, and mill torque [30]. The focus on the variables governing the dewatering mill would be the best route to take in the monitoring of the mill's performance for reduced bagasse moistures. In particular, the mill torque and mill lift are considered more important to monitor as they indicate slippage or reabsorption [22,45]. Reabsorption is when bagasse that is already deprived of its water, reabsorbs water as it passes the axial plane of the rollers, thereby increasing the bagasse moisture [22]. The re-absorption factor can be calculated from the overall mass balance of the extraction plant shown in Figure 5-8.

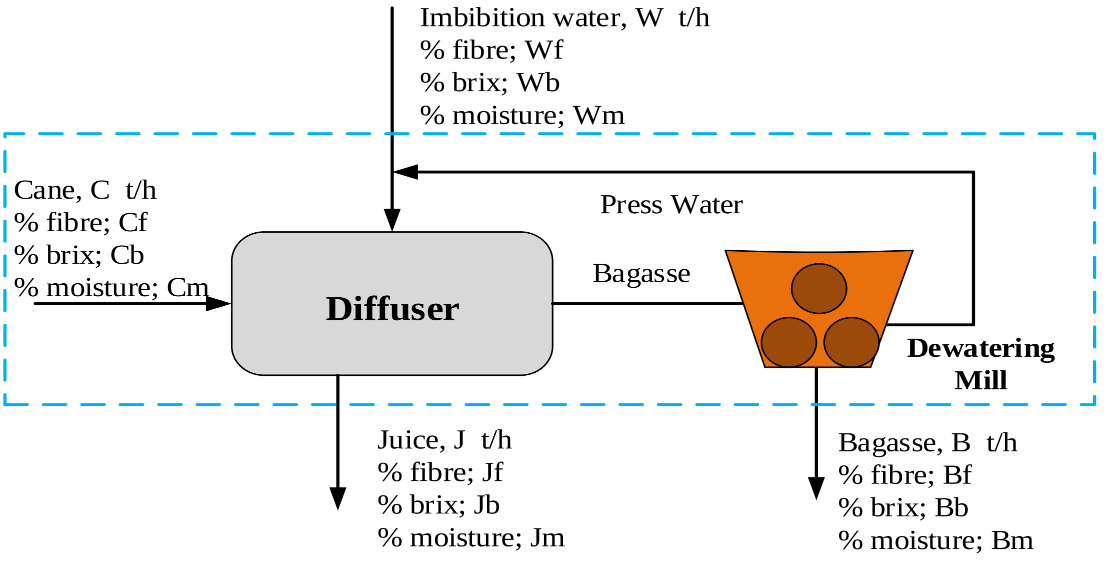

Figure 5-8: Typical overall extraction plant material balance

The symbols B, C, J, and W represent the flowrates of bagasse, cane, draft juice, and imbibition water. From the mill setting variables and the mass balance deduced variables, like the bagasse flow rate, % Brix or DS content, % fiber, and % moisture, the re-absorption factor is:

$$\text{Re} - \text{absorption factor} = \text{Bagasse volume } (B_V)/\text{Escribed volume } (E_V) \qquad (5\text{-}9)$$

The escribed volume is the generated volume at the delivery opening between the roll mills [22]. The monitoring of the re-absorption factor of the dewatering mills will help in the early detection of unreasonably high re-absorption factor values, thereby promoting early corrective action and the reduction of the bagasse moisture content. Furthermore, reabsorption implies that energy was expended to remove water in the bagasse only for it to be reabsorbed at the dewatering mill exit. This aspect of the impact of reabsorption on energy wastage in the dewatering mills is often overlooked in literature studies. However, based on the present study results it is considered important to evaluate the impact of reabsorption from the view of energy wastage in both the dewatering mill and the boiler unit. Such awareness of the role of reabsorption is important for formulating optimal control strategies for both the boiler and dewatering mill.

5.4. Conclusions

Energy indicators that allow the capturing of the relevant variables in the operation of the boiler and deaerator system were defined. A modified steam-generating cost index was presented which allows for the inclusion of the feedwater supply aspects to the deaerator unit to be accounted for. The Aspen Plus® simulation of a typical cogeneration system in sugarcane mills was used to conduct sensitivity analysis aimed at identifying the process variables whose steady-state value variation results in inefficiencies in the operation of the boiler and the deaerator. Bagasse moisture, flue gas temperature, and oxygen concentration are the process variables considered for the boiler unit sensitivity studies. For the deaerator, the return condensate and cold make up water flows and temperature variations were considered. A 5% steady-state deviation in the bagasse moisture content was observed to have the largest effect on the boiler operation and economics as compared to similar deviations in the flue gas temperature and oxygen concentration. A 5% reduction in bagasse moisture content resulted in a US$2.40/hr reduction in the cost of generating HP steam and a potential surplus bagasse revenue gain of US$280/hr. A 2% increase in the return condensate temperature resulted in a 3.1 kg reduction in deaerator steam reduction per tonne boiler feedwater. The return condensate temperature and the percentage of cold make up water used were shown to account for approximately 3% of the steam-generating cost. Hence for improved operation and economics of the boiler and deaerator the monitoring of reabsorption in the dewatering mill and the optimal insulation of the feedwater supply system is recommended.

Acknowledgments

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Chapter 6

6. Set-Point Optimization for Plant-Wide Control of a Sugarcane Mill Under Process and Market Price Disturbances: Energy and Economic Perspectives

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The objective of the dissertation in this chapter and the summary findings

In this chapter, objectives 3 and 4 are addressed. Objective 3 involves the use of the Monte Carlo approach to evaluate the impact of external process and market price disturbances on the energy and economic efficiency of a sugarcane mill. Objective 4, on the other hand, seeks to mitigate the observed steady-state effects in Objective 3 through the implementation of set-point optimizing control. For the given values of the external disturbances, the goal of set-point optimization is to maximize factory profitability, by finding new optimal set-points for the CVs. Fourteen CVs including those observed from Chapters 4 and 5 to have a significant influence on energy efficiency, were selected for use as decision variables in the set-point optimizer, while optimality was defined in terms of the net-revenue. Energy indicators defined in Chapters 4 and 5 with some additions from the literature were used to evaluate the benefits of set-point optimization.

Overall improvements were observed in the energy and economic efficiencies of the sugarcane mill operations, as a result of set-point optimization with the selected CVs. The total vapor demands of the extraction, clarification, and crystallization unit were reduced by 14% with the implementation of set-point optimization. The coupling of the evaporator unit with the batch vacuum pans through vapor supply is known to be one of the barriers to the efficient operation of the evaporator unit. Increased massecuite recycling in the vacuum pans is one of the reasons for the high and erratic vapor demands of the crystallization unit. By using set-point optimization 23% reductions in massecuite recycling were observed while available surplus bagasse and the net revenue increased by 8.5 and 2.4 %, respectively. Out of the 14 CVs considered, 9 CVs were observed to have optimal set-points that are robust and resilient to variations in the external process disturbances and market prices. Hence these 9 CVs are ideal candidates for implementing self-optimizing control for the sugarcane mills while simplifying operation by only doing set-point optimization for the remaining 5 variables.

SOM refers to the supplementary material for this chapter, which is found in Appendix C.

Declaration by the candidate

With regards to Chapter 6, the nature and scope of my contribution were as follows:

Nature of contribution	The extent of contribution (%)
Project and scope definition, analysis of data, interpretation of results, and writing of chapter	80

The following co-authors have contributed to Chapter 6.

Name	e-mail address	Nature of contribution	Extent of contribution (%)
J.F. Görgens	jgorgens@sun.ac.za	General technical discussions and provided writing assistance through the review of the chapter.	5
T.M. Louw	tmlouw@sun.ac.za	Assisted in the development of the chapter scope. Provided continuous review and proofreading of the chapter.	5
L.Auret	lauret@sun.ac.za	Assisted in the development of the chapter methods as well as proofreading of the chapter.	5
M.A. Mandegari	mandegari@sun.ac.za	Assisted in the development of the chapter scope. Provided continuous review and proofreading of the chapter.	5

Signature of candidate:

Date: March 2021

Declaration by co-authors:

The undersigned hereby confirm that

1. the declaration above accurately reflects the nature and extent of the contributions of the candidate and the co-authors to Chapter 6

2. no other authors contributed to Chapter 6 besides those specified above, and

3.potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 6 of this dissertation.

Signature	**Institutional affiliation**	**Date**
	Stellenbosch University	
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Set-point optimization for plant-wide control of a sugarcane mill under process and market prices disturbances: Energy and Economic Perspectives

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Abstract

Optimization and control strategies are necessary to keep factory operations profitable while minimizing energy usage. For sugarcane factories, the operational drive towards improved energy efficiency and profitability is often interrupted by the random variations of the process and market price disturbances. Therefore, the study aims to present a plant-wide steady-state optimal operation policy for implementation in sugarcane mills when process and market price disturbances occur. The strategy uses a set-point optimizer based on a surrogate optimization algorithm to find optimal set-points for 14 controlled variables, which the controllers attempt to implement such that maximum revenue is achieved when disturbances occur. Monte Carlo simulations are used to randomly sample from the predefined disturbance distributions and to simulate using the sugarcane mill and financial models. To assign an economic value to optimal plant-wide control, the financial model defines the net-revenue as the difference between the product revenues and the raw materials expenditure. With set-point optimization, surplus bagasse increased by 8,5% with an acceptable sugar yield reduction of 0.45% and a net revenue increase of 2.4 %. Therefore, the optimizer managed to find the global optimal points at which the loss in surplus bagasse revenue due to excess energy use (to minimize sugar loss) no longer justifies the revenue gain from sugar. Considering, the global shift towards bio-based products, the increase in available surplus bagasse, and the 6.4% decrease in HP steam usage make it possible for a relatively large bio-refinery that uses bagasse as feedstock to be annexed to a set-point optimized sugarcane factory.

Keywords: Monte Carlo simulation; Set-point optimization; Sugarcane mill; Energy efficiency; Steady-state operation; Surrogate optimization

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6.1. Introduction

Sugarcane is an important crop that has made a major contribution to the gross national product of many developing countries such as China, Brazil, India, Thailand, and South Africa [1]. With increased volatile sugar markets in recent years, there is growing interest from the sugar industry to diversify its revenue stream from sugar production through the valorization of the main by-products: molasses and bagasse [1]. This need coincides with the increasing demand for bagasse as a key feedstock in the large-scale commercialization of renewable energy, biofuels, and bio-chemicals [2]. All steady-state process energy demands to produce sugar may be met from bagasse while generating surplus bagasse for use in the production of renewable electricity [1], biofuels [3], and biochemicals [4]. In the past, sugar mills were operated and designed to use more bagasse to avoid costs associated with excess bagasse disposal, which had no alternative justifiable use [1]. The shift in the economic drivers of the sugar industry has prompted several studies that evaluate different designs [5], operating practices [6], and bio-refinery pathways [3]. These studies seek to increase the supply of bagasse and molasses for valorization while reducing energy usage and sugar production losses.

However, the operational drive towards improved energy and economic efficiency is often interrupted by the random and unavoidable variation of the process disturbances and market prices [6]. These random variations have an impact on the steady-state operation and economics of a sugarcane factory. Hence these random variations must be considered in formulating design and control solutions for the sugarcane mill. However, for the optimal design and control solution of sugarcane mills, most studies assume fixed or seasonal-averaged values for the disturbance variables, despite the acknowledgment of their day-to-day variation [7]. Although such evaluations can be useful, they provide no information about the actual factory behavior when variations in the process and market price disturbances occur. Also, important system trends can be missed, and the resulting solutions are only optimal for the average values used.

To overcome these shortcomings, the aim of this study is twofold. Firstly, the Monte Carlo approach is used to investigate the effect of random variations in the process disturbances and market prices on the steady-state factory operation and economics. The Monte Carlo simulations' approach is to randomly sample the model input values from their probability distributions, which follow their real-life factory variations [8]. In this study, 5000 random values of the process and market price disturbances are taken from their probability distributions and simulated using the sugarcane mill and financial models, respectively. The sugarcane mill model includes the steady-state mass and energy balance of an entire sugarcane mill and is used to quantify the effect of the process disturbances on factory operation. Sugarcane flow, sucrose, fiber, and dissolved solid concentrations as well as air temperature and humidity are considered as the external process disturbances in this study. The financial model is the net revenue which considers the difference between the product revenues (sugar, molasses, and surplus bagasse) and the raw materials expenditure (sugarcane and lime).

The second study aim is to evaluate the improvements in factory economics and energy usage when set-point optimization is done with the occurrence of process and market price disturbances. Set-point optimization is a technique that allows for the evaluation of the operating conditions to find the optimal set-point values for the controlled variables (CVs) when disturbances occur [9]. Optimality is defined in terms of the factory net revenue and 14 CVs considered important in the operation of a sugarcane factory are selected for use as decision variables in the optimizer. Surrogate optimization algorithms are used for set-point optimization as they can handle black-box optimization problems where multiple local or global optima might exist [10]. Although set-point optimization has been applied for improving the control of distillation columns [9], there are no known studies that have applied the concept for the plant-wide control of sugarcane mill operations. Therefore, this study seeks to investigate the attainable economic and energy efficiency improvements when online set-point optimization is used for plant-wide optimal control of the sugarcane mill operations when process and market price disturbances occur.

6.2. Methods

6.2.1. Sugar mill model description

The MATLAB sugar mill model developed by Starzak and Davis [11] for a typical sugarcane mill that processes 250 tonnes of cane/hr under steady-state conditions is used in this study. The MATLAB sugar mill model was successfully verified and validated against the results from the commercial process flow sheeting software Sugars® for the same input data and actual factory operations of seven sugarcane mills [11]. Figure 6-1 provides a block diagram of the MATLAB sugarcane mill configuration consisting of the extraction, clarification, evaporation, crystallization, sugar drying, and utility operations.

The first step in sugar production is the knifing and shredding of sugarcane in preparation for sucrose extraction in the diffuser (extraction unit). After sucrose extraction, the remaining fiber residue (bagasse) is dewatered to reduce its moisture content before incineration in the boiler [6]. The juice from the extraction unit named draft juice (DJ) is mixed with syrup filter sludge and filtrate juice before being heated consecutively in three heaters [11]. The heating of the mixed juice (MJ) is crucial for effective juice flashing and settling of juice impurities in the clarifier [12]. The clear juice (CJ) from the clarifier is directed to the evaporator unit where it is first pre-heated to allow for flashing upon entry in the first evaporator effect [12]. The CJ is consecutively concentrated in five-evaporator effects to form concentrated syrup which is fed to the crystallization unit for evaporative and cooling crystallization.

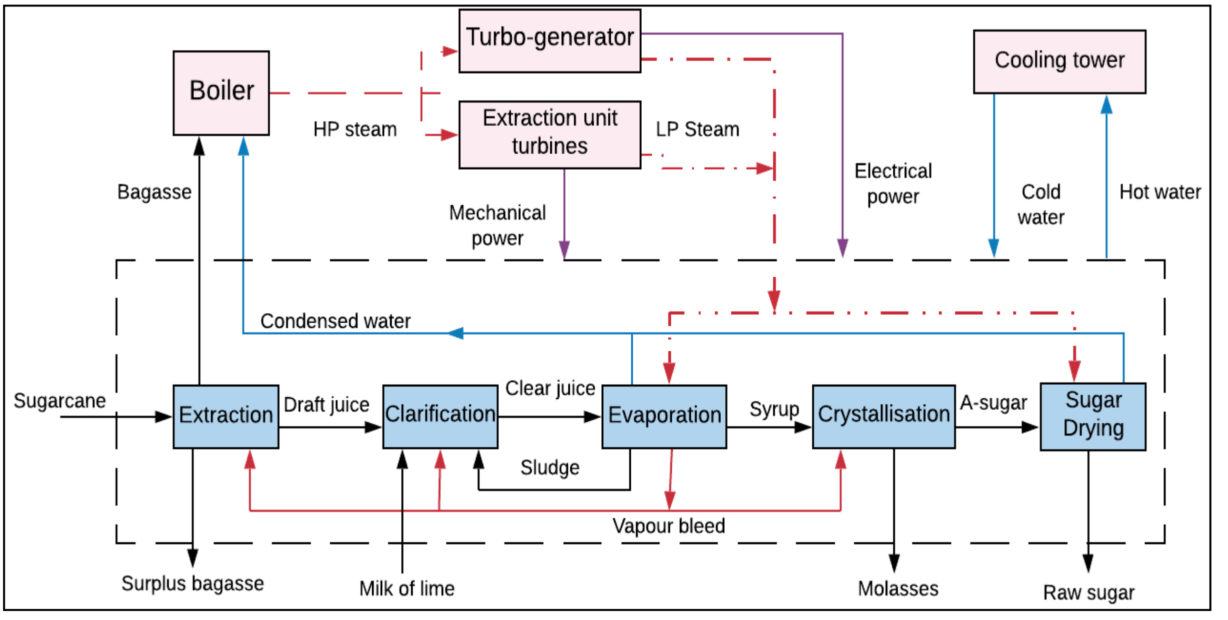

Figure 6-1: Simplified process flow diagram of a sugarcane mill

A three-pan boiling, and cooling crystallization scheme (A, B, and C) is used to ensure maximum sucrose recovery [1,13]. Only the first stage sugar (A-sugar) is used commercially hence it is further dried in the sugar dryer. The B and C-sugar streams are used to produce seeding material for use in the growth of sucrose crystals in the A-pan [12]. At each stage, centrifuges are used to separate the sugar from syrup and the resulting non-product streams termed molasses are recycled to the next pan stages while the C-molasses stream is a by-product. The utility section comprises the boiler, turbogenerator, and cooling tower for high-pressure (HP) steam, electricity, and cooling water production, respectively. The HP steam is mainly used in the turbogenerator with a small portion extracted for use in the extraction unit turbines. The low-pressure (LP) steam from the turbines and the turbogenerator is used in the first evaporator effect and sugar drier. The terms HP and LP steam are used to distinguish the boiler unit steam at 31 bars from the exhausted steam of lower pressure. The vapor demands of the extraction, clarification, and crystallization unit are sustained by the vapor from the evaporator unit [11].

6.2.2. Financial model

To quantify the operational profitability of the sugarcane factory, the net revenue is considered and is coded in MATLAB 9.7 as the difference between the product revenues and the raw materials expenditure (Equation (6-1)). The symbols F and P denote the flow and price associated with the product and raw material streams, respectively.

$$\begin{aligned}\text{Net revenue (US\$/hr)} &= (F_{SUGAR} \times P_{SUGAR} + F_{MOLASSES} \times P_{MOLASSES} \\ &+ F_{SURPLUS\ BAGASSE} \times P_{SURPLUS\ BAGASSE}) \\ &- (F_{CANE} \times P_{CANE} + F_{LIME} \times P_{LIME})\end{aligned} \tag{6-1}$$

The production cost has been associated with the raw material value of sugarcane and lime. Sugarcane consists of 70% water, therefore, in theory, there is a surplus provision of water in a sugarcane mill [12]. Bagasse is used to sustain the process steam and electricity demands of a sugarcane factory. For these reasons, the utility (water, steam, and electricity) costs are considered zero in this study. The effect of the external process disturbances and market variations on the costs related to labor and routine maintenances is assumed to be negligible, in the present study. With efficient steady-state operating measures, all the steam demands can be met with the available bagasse, while simultaneously generating surplus bagasse for use as an additional revenue stream [6]. Hence, along with raw sugar and molasses, surplus bagasse is considered a revenue stream. The use of surplus bagasse in Equation (6-1) provides a vital weighting factor for a balance between energy usage and sugar production using their market values.

6.2.3. Statistical analysis and sampling

Given the data of a random variable, a probability distribution function (PDF) is used to describe all the possible values and likelihood that a random variable can take within a given interval [14]. The descriptive statistics (mean and standard deviation) of the historical data for each considered variable in this study is used to obtain their corresponding PDFs. The Kolmogorov–Smirnov (K-S) test is used to test the goodness of fit of the analytical PDF fitted to the given data. In the K-S test, the maximum absolute difference between the empirical CDF of the collected data and the theoretical CDF of a reference distribution is computed [15]. The obtained difference is compared to the critical value derived at a significance level of 0.01. If the K-S test statistic is larger than the critical value, the null hypothesis is rejected meaning the collected data does not fit well with the population from a reference distribution. This procedure is repeated for different reference distributions until a distribution is found which best suits the data.

When sampling more than one random variable, an independence test is done to ascertain if an outcome in one sample space influences the occurrence probability of other events [16]. If two variables X and Y are independent, then their covariance is zero. However, a covariance of zero does not necessarily mean that two variables are independent. Two random variables X and Y are independent if the product of their univariate probability densities $f_x(X)$ and $f_y(Y)$ is equal to the joint probability density $f_{x,y}(X, Y)$, for all x and y values [16]. Therefore, to ensure there is no dependence within the random variables, an independence test is done. If two or more random variables are found to be dependent, a joint (multivariate) distribution is used instead to describe their probability of occurrence. To randomly sample from the resultant distributions, the inverse transformation method is used based on a built-in MATLAB function, which allows for thousands of random numbers to be generated from a predefined distribution. The inverse transformation method is based on the observation that the continuous CDF ranges uniformly between 0 and 1 [15]. Thus the inverse of the CDF is employed to generate the random values X from the probability distribution function such that, X= CDF^{-1} (U) where U is a random number between 0 and 1.

6.2.4. Probability distributions for process disturbances

Measures are taken during production to minimize sugar yield losses in an energy-efficient manner. However, these measures are interrupted by the random variation of the process disturbances associated with sugarcane quantity, sugarcane quality, and climate conditions [6,17]. The following sections describe the considered process disturbances and their PDFs.

6.2.4.1. Sugarcane quantity

Lower sugarcane flow rates can be experienced in a sugarcane mill due to sugarcane supply and operating problems [12]. In other instances, when a factory is behind its sugar production schedule higher sugarcane flows are required. Both scenarios can have a detrimental effect on the overall factory energy balance and profitability [12]. Therefore, to study the impact of sugarcane quantity variations, the annual review reports of the 2010 to 2018 sugar milling season in Southern Africa were used to obtain historical data on typical sugarcane flows [18–25]. Based on the K-S test results the data for the sugarcane quantity was found to be normally distributed (Figure 6-2) and 5000 random values were generated for use as inputs in the MATLAB sugar mill model.

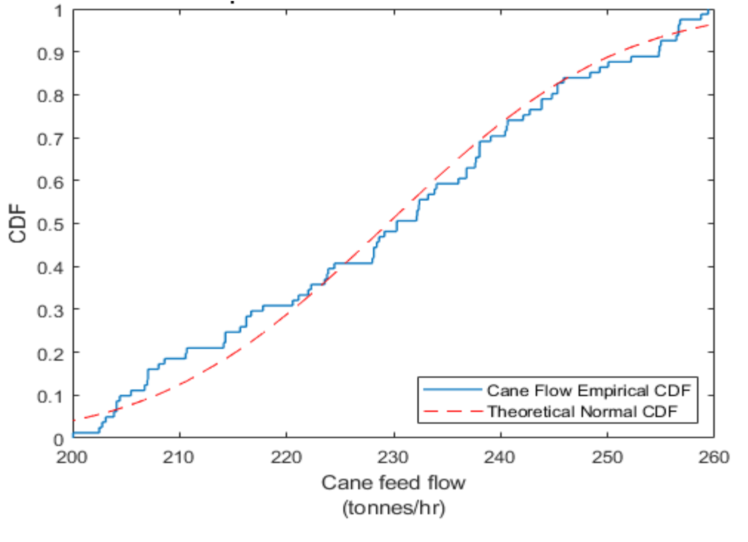

Figure 6-2: Comparison of the empirical CDF plot for cane feed flow data with the theoretical normal CDF

6.2.4.2. Sugarcane quality

Sugarcane quality variations have been attributed to several factors, ranging from the genetic potential of the cultivars, climatic conditions, and agricultural management [12]. After the sucrose extraction process, sugar recovery is dependent on juice purity but the high non-sucrose content of the incoming sugarcane results in high juice turbidity and poor clarification rates [12]. The high dissolved solids content of sugarcane is responsible for the high ash content of bagasse and the lowering of its calorific value [5]. This reduces both boiler efficiency and the availability of surplus bagasse for additional revenue. Therefore, the sugarcane quality variables considered for this study are the mass percent of sucrose, dissolved solids, and fiber. Dissolved solids (DS) content refers to all the solute material (sucrose and non-sucrose) in a solution. The sugarcane sucrose, DS, and fiber content values reported for the year 2010 to 2018 in the sugarcane mills [18–25] were used for this study. The independence test showed dependence among the sugarcane sucrose, DS, and fiber content. Therefore, a multivariate normal distribution for the sugarcane quality variables was applied. Often the univariate tests are used to conduct multivariate normality tests based on the fact that the marginal distributions making up a multivariate normal distribution should be univariate normal [26,27]. From the K-S test, the individual distributions of the sugarcane quality variables were found to be normally distributed (Figure 6-3), hence this was used as a satisfactory indication of a good fit for the multivariate distribution. The covariances of the multivariate distribution were used to take 5000 random samples for each sugarcane quality variable.

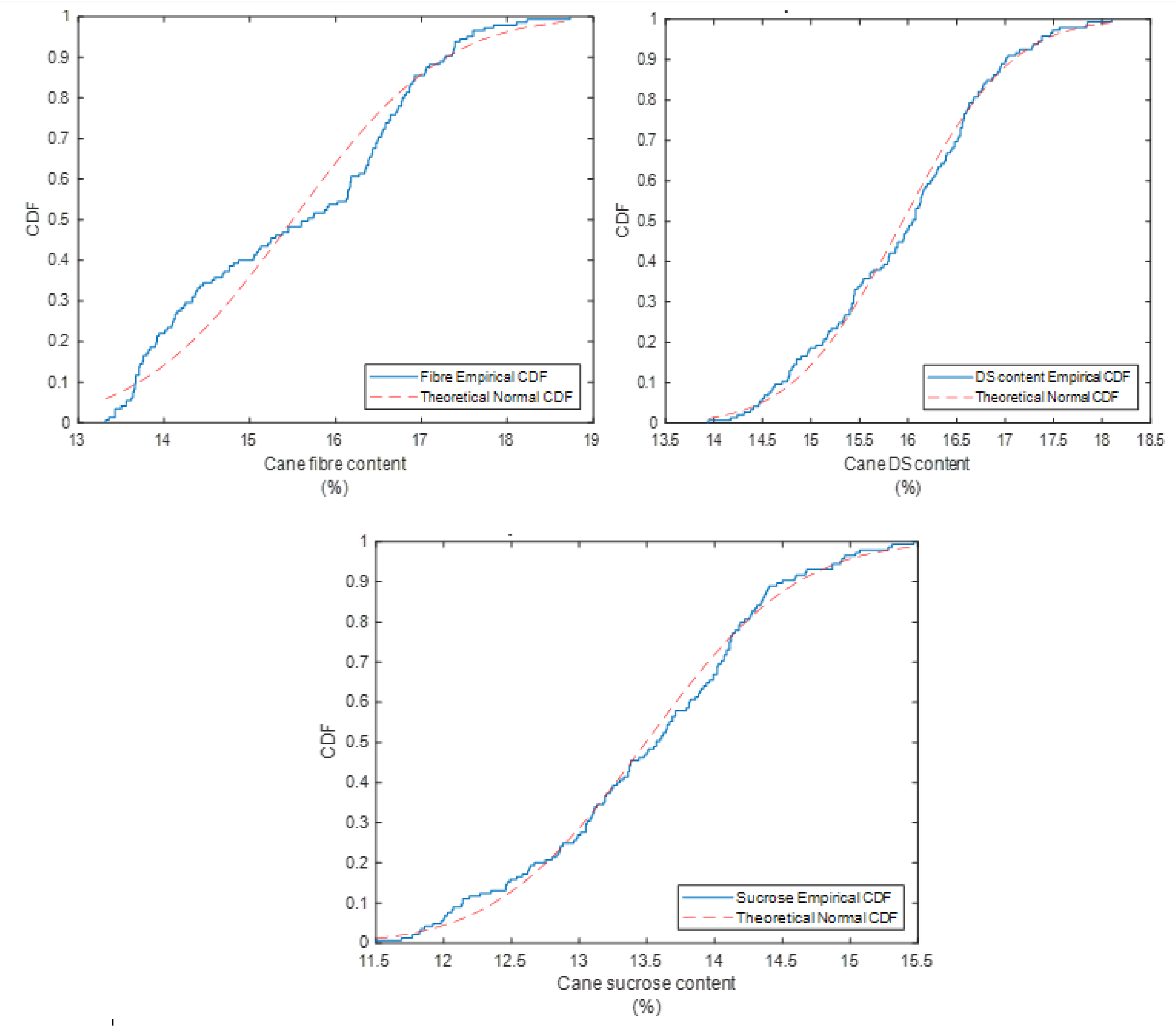

Figure 6-3: Empirical and theoretical CDF plots for sugarcane fiber, DS, and sucrose content

6.2.4.3. Air humidity and temperature

Climatic conditions can have a detrimental impact on the performance of the cooling tower and sugar drier. Air is used for combustion in the boiler and evaporative actions in the sugar drier and cooling tower [12]. However, in the MATLAB sugar mill model, the use of air is only included in the sugar drier [11]. To prevent the microbiological degradation of sucrose and to meet customer specifications, the sugar moisture is reduced in the drier [12]. Because saturated steam is used to heat the air, more heating steam is required when the air temperature is low, and the relative air humidity is high. The historical climate data of the South African sugarcane mill regions in the year 2010 to 2018 [28–30] was used to acquire the air temperature and humidity values. Both air temperature and relative humidity were observed to be normally distributed (Figure 6-4). Dependence was observed between air humidity and temperature data, hence a bivariate normal distribution was attained. The histogram plot for sugarcane quantity and the marginalized histogram and scatter plots for the multivariate and bivariate distributions are given in SOM, Figure S1.

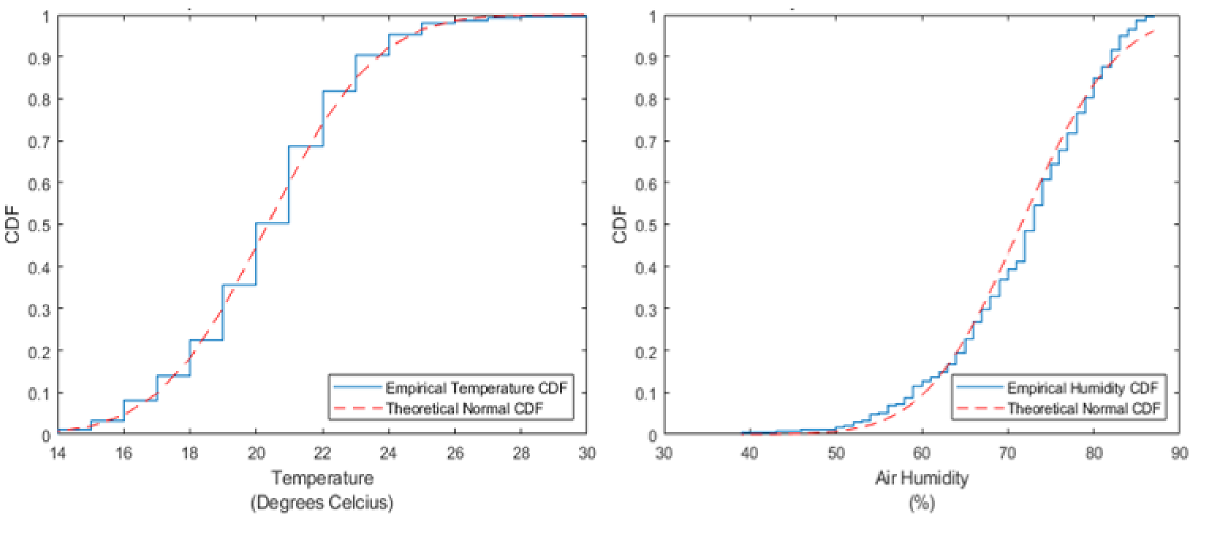

Figure 6-4: Empirical and theoretical CDF plots for air temperature and humidity

6.2.5. Probability distributions for market prices

Based on the defined financial model in Equation (6-1), the market prices of the sugarcane factory raw materials and products are considered in this study. Monthly data from January 2008 to July 2019 were used for the sugarcane, coal, transportation, and sugar market prices. Due to a lack of data, yearly average values from 2008 to 2019 were used for lime.

6.2.5.1. Quicklime price

Quicklime is used to make milk of lime which in turn is used for pH control and to aid the settling of the mixed juice impurities in the clarifier [12]. Quicklime is used to make milk of lime which in turn is used for pH control and to aid the settling of the mixed juice impurities in the clarifier [12]. This often entails the use of a mixing tank where the quicklime is continuously agitated while adding the hot condensates [12]. The resulting mixture is screened in a coarse screen conveyor, while the lime slurry is overflowed to a tank where further addition of condensates is done until the milk of lime of required concentration is attained [12]. Lime prices [31] were found to be normally distributed (Figure 6-5) and 5000 random values were sampled from the PDF.

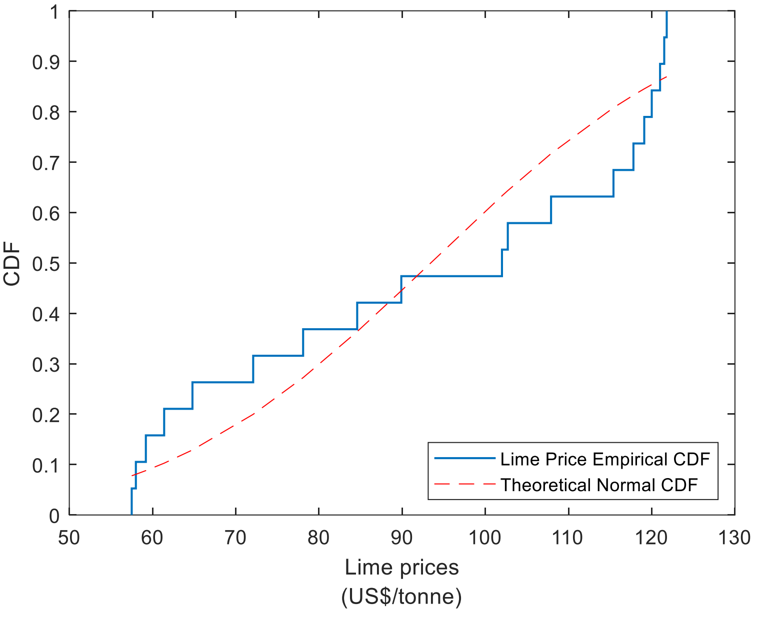

Figure 6-5: Empirical and theoretical CDFs for the lime price

6.2.5.2. Sugarcane price

To incentivize the sugarcane growers for good sugarcane quality, the South African sugar industry adopted the recoverable value payment system [12]. This system is based on the view that the amount of recovered sugar from sugarcane is not solely dependent on the sucrose content but also on the sugarcane non-sucrose and fiber content. This payment system also observes that the sugarcane non-sucrose and fiber content have some value to the sugar manufacturers through the sale of molasses and the use of bagasse for the factory energy demands [12]. As a result, the recoverable value (RV) in the sugarcane is calculated as a function of the sugarcane sucrose, non-sucrose, and fiber content to consider the sucrose losses from the molasses and bagasse streams. Equation (6-2) denotes the formula for RV calculation as a percentage of the sugarcane [13].

$$\text{Recoverable value (RV)}\,,\% = x_{S,cane} - 0.35x_{NS,cane} - 0.02x_{F,cane} \qquad (6\text{-}2)$$

Where $x_{S,\ cane}$, $x_{NS,\ cane}$ and $x_{F,\ cane}$ represent the sugarcane sucrose, non-sucrose, and fiber contents as a percentage of sugarcane. From Equation (6-2), the total tonnage of recoverable value is determined as shown in Equation (6-3):

$$\text{Total recoverable value(RV) in tonnes} = \text{Tonnes of sugarcane} \times \text{RV (\%)} \tag{6-3}$$

From Equation (6-3) and the industry determined RV prices [32], the price of sugarcane is:

$$\text{Sugarcane price, (US\$/tonne sugarcane)} = \text{RV price} \times \text{Total RV tonnes} \tag{6-4}$$

6.2.5.3. Sugar and molasses prices

Although sugar is the main product of a sugarcane mill, the resultant C-molasses can be used to produce ethanol, succinic acid, and other bio-based products [33]. The world raw sugar market prices from the year 2008 to 2018 were collected [34]. Data for molasses prices are limited. Hence the price of molasses is calculated from the value of sugar-based on their sucrose content ratio.

6.2.5.4. Surplus bagasse price

The value of bagasse to a sugarcane factory is dependent on the type of supplementary fuel (coal), which would otherwise be used in case of bagasse deficiency. Hence the combined cost of buying and transporting coal to a sugarcane factory is used to determine the selling price of surplus bagasse based on the calorific value differences between coal and bagasse. The method used for assigning the bagasse price is considered a conservative estimate as the development of sugarcane biorefineries can potentially increase the value of bagasse. The coal and transportation prices were obtained from [35–37]. The average transportation distance of coal was estimated to be 90 kilometers. Dependence was observed amongst the coal, transportation, sugar, and sugarcane prices. Therefore, a multivariate normal distribution of these four variables was fitted and 5000 random samples were taken for each variable. The empirical CDFs for RV, sugar, coal, and coal transportation prices are provided in Figure 6-6. The histogram plot for lime price and the marginalized histogram plots for the multivariate distribution of the other market prices is provided in SOM, Figure S2.

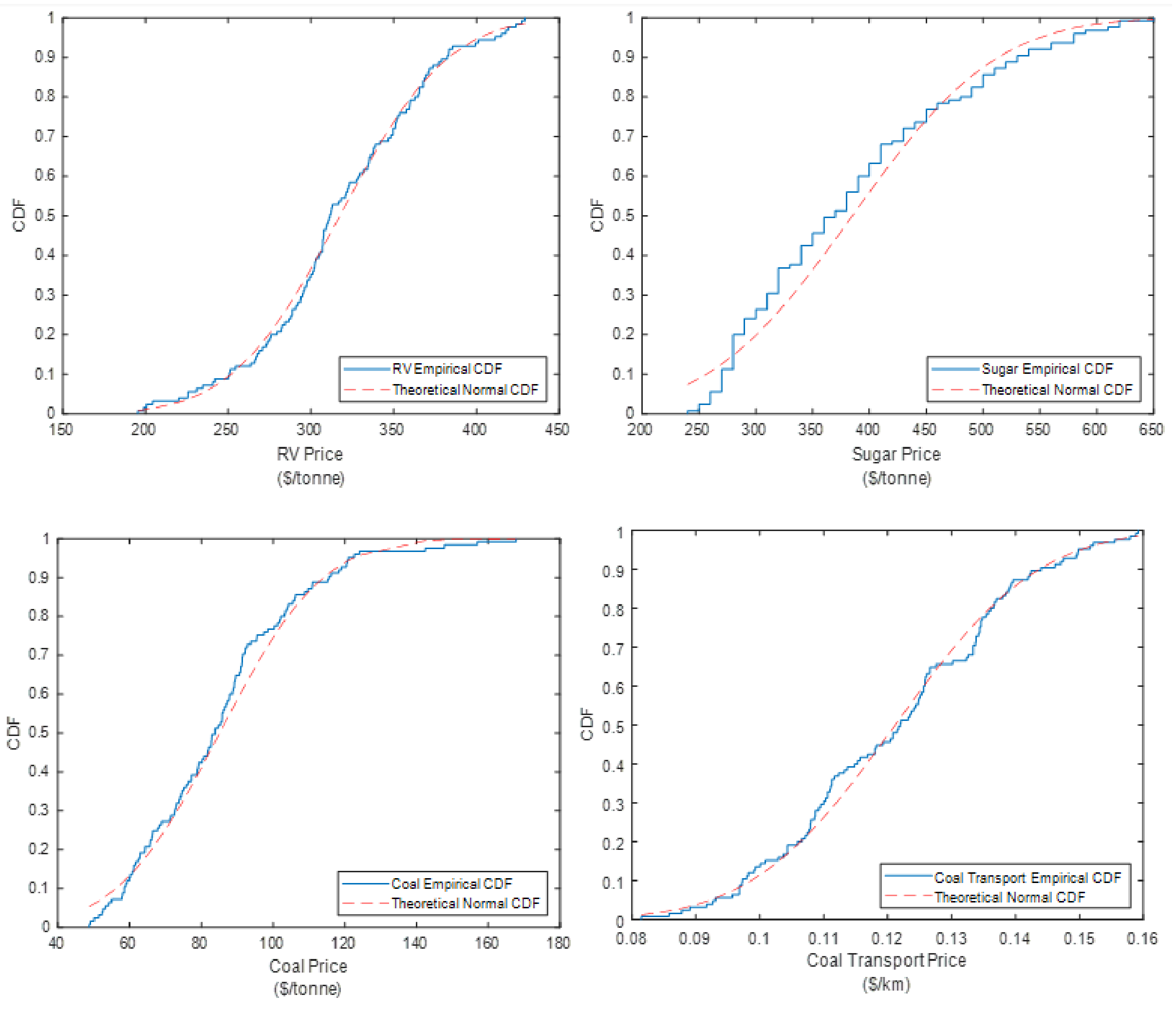

Figure 6-6:Empirical and theoretical CDFs for the market values of RV, sugar, coal, and coal transportation

6.2.6. Set-point optimization

Most studies assume that the uncertain variables are fixed at their seasonal-averaged values to find the appropriate set-points for the controlled variables. This implies that constant set-points are used for the CVs despite the acknowledgment of the inherent randomness in the disturbance variables during actual factory operation. Hence instead of using the constant CVs set-points, set-point optimization seeks to recompute new optimal set-points for the CVs with the variation in the process disturbances and market prices. In practice, the implementation of set-point optimization can be done either online or offline depending on whether online or laboratory measurements are used for obtaining the disturbance data. While online set-point optimization provides better results, for a factory with no online measurements of the disturbances the optimization problem can be scheduled offline by considering their measurement intervals, frequency of variation, and effect on factory operations. To illustrate the benefits of set-point optimization which can be implemented online or offline in practice, 5000 randomly generated values of the process disturbances and market prices are used (Figure 6-7), to simulate the behavior of the actual sugarcane factory operations under such variations. Figure 6-7 shows the proposed set-point optimization structure for sugarcane mills.

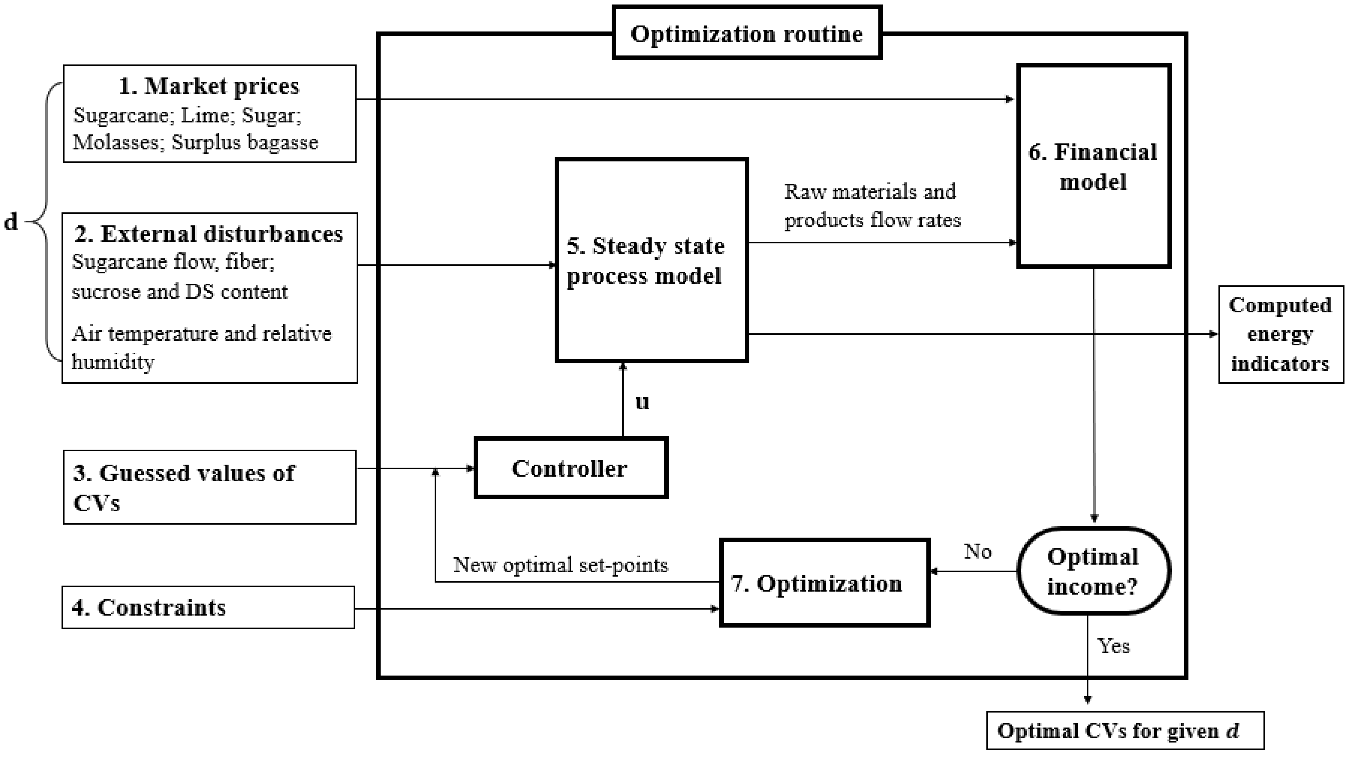

Figure 6-7: Proposed set-point optimization structure for the sugarcane mills. The d and u denote the process disturbances and manipulated variables, respectively.

An optimization problem has three components: the objective function, decision variables, and constraints. An objective function is the scalar performance indicator that needs to be minimized or maximized by adjusting the decision variables while considering the factory constraints. For this study, 14 CVs are selected as decision variables while the net-revenue is the objective function to be maximized. Set-point optimization uses the interaction between the optimization and local control layer to recompute new optimal set-point values which the controller attempts to implement in factory operation.

6.2.6.1. Controlled variables and factory constraints

Based on the review of previous studies, 14 CVs that are considered to influence factory operation were selected in this study for use as decision variables in set-point optimization [6,17]. Table 6-1 provides a list of these CVs and their allowable operating regions [6,17].

Table 6-1: CVs and operating constraints used for set-point optimization

Control variables	**Lower**	**Upper**	**Units**
Extraction and clarification			
Press water temperature after heating	65	84	°C
MJ temperature after primary heating	70	85	°C
MJ temperature after secondary heating	91	97	°C
MJ temperature after tertiary heating	102	108	°C
Evaporation			
CJ temperature from the preheater	110	116	°C
Final syrup DS	57	72	%
Crystallization			
A- massecuite DS	90	94	%
A- massecuite temperature	61	74	°C
B- massecuite DS	92	96	%
B- massecuite temperature	61	74	°C
C- massecuite DS	93	98	%
C- massecuite temperature	61	74	°C
Re-melt DS	60	80	%
Re-melt temperature	60	80	°C

6.2.6.2. Surrogate algorithm for set-point optimization

A global optimization algorithm is required to handle black-box set-point optimization problems where there might exist multiple local or global optima. The surrogate optimization algorithm in MATLAB was selected which uses quasi-random points that fall within the bounds of the controlled variables for the evaluation of the process models with low computation speeds [10]. A surrogate model is constructed by interpolating a radial basis function through the random points, such that $s(x) = f(x) + e(x)$, where s(x) is the surrogate model prediction at x, f(x) is the output from the computationally expensive model, and e(x) the error term [10]. During the optimization procedure, information attained from the surrogate model is used to guide the search for the minimum of the objective function by sampling several random points close to the point with the smallest objective function value, this far.

The solver uses these points to search for a minimum of the weighted combination of the scaled surrogate and the distance of the existing search points [10]. The point with the minimum value is used to evaluate the computationally expensive model and update the surrogate. Therefore, the surrogate algorithm used in this study for the steady-state set-optimization of the black-box sugarcane mill model alternates between the construction of the surrogate and the search for minimum phases. This enables it to balance between exploration and speed by only evaluating the expensive model at carefully selected points. Parallel computing and three computers (SOM, Table S-1) were used to further reduce the time it takes to run each of the 5000 set-point optimization routines. Only 1851 optimizer updates failed to converge to a solution.

6.2.6.3. Evaluation of energy efficiency improvements

To evaluate the corresponding energy efficiency enhancements attainable with set-point optimization, the energy indicators commonly used in the sugarcane industry for energy monitoring and benchmarking are used and given in Table 6-2. The symbols $\dot{m}$, Δh_{VL} and w represents the mass flow rate, the specific heat of evaporation, and the component weight percent, respectively. Therefore, the distributions of the output variables are used to calculate these energy indicators before and after set-point optimization, to quantify the attainable benefits of steady-state set-optimization when process and market price disturbances occur.

Table 6-2: Energy indicators selected for use in the quantification of energy efficiency [6,17]

Category	Energy Indicators	Units and a brief description
Process unit view		
Clarification	$\frac{\sum_{i=1}^{3} \dot{m}_{vapor(i)} \times \Delta h_{VL(i)}}{\dot{m}_{sugarcane}}$	$kWh/tonne\ sugarcane$ Total energy used by the mixed juice (MJ) heaters.
Evaporator	$\frac{\dot{m}_{LP\ in,1^{st}\ effect} \times \Delta h_{VL}}{\sum_{i=1}^{5} \dot{m}_{total\ evaporated\ water}}$	$kWh/kg\ evaporated\ water$ Thermal energy to 1st effect relative to total evaporated water in all 5 effects.
Crystallization	$\frac{\sum_{i=1}^{3} \dot{Volume}_{,massecuite\ (i)}}{\dot{m}_{MJ} \times w_{MJ,DS\ content}}$	$m^3/tonne\ MJ\ DS\ content$ Measure for the extent of massecuite recycling.
Factory overview		
HP steam usage	$\frac{\dot{m}_{total\ HP}}{\dot{m}_{cane\ crushed}}$ $\frac{\dot{m}_{total\ HP}}{\dot{m}_{sugar}}$	$tonnes\ \ HP\ steam/tonne\ sugarcane$ and $tonnes\ \ HP\ steam/tonne\ sugar$. HP steam is used for processing sugarcane and producing sugar.
Vapor bleed usage	$\frac{\sum_{i=1}^{10} \dot{m}_{vapor(i)}}{\dot{m}_{sugarcane}}$	$tonnes\ \ vapour/tonne\ sugarcane$ Vapor demand from the evaporator unit.

6.3. Results analysis and discussion

In this section, firstly the effect on the energy performance of the clarification, evaporation, and crystallization unit brought on by variations in the process disturbances and market prices is investigated and the attained improvements under set-point optimization are evaluated. Secondly, to provide an overall outlook of the energy and economic performances, the HP steam demand, net-income, and product distributions are analyzed for both set-point optimized and non-optimized operation.

6.3.1. Clarification unit

Three heat exchangers (primary, secondary, and tertiary) are used to heat the mixed juice (MJ) to slightly above 100 ℃ to permit effective flashing [12]. Flashing removes the air bubbles from the suspended particles, which if not removed would otherwise affect the settling of suspended solids in the clarifier [12]. Extensive vapor bleeding from the evaporator unit is done to sustain the heating demands of the clarification heaters. Figure 6-8 shows the sensitivity of the total heat duty of the heaters to the variation in the process disturbances. The percentile values of the disturbances and their summary statistics are provided in SOM, Table S-2.

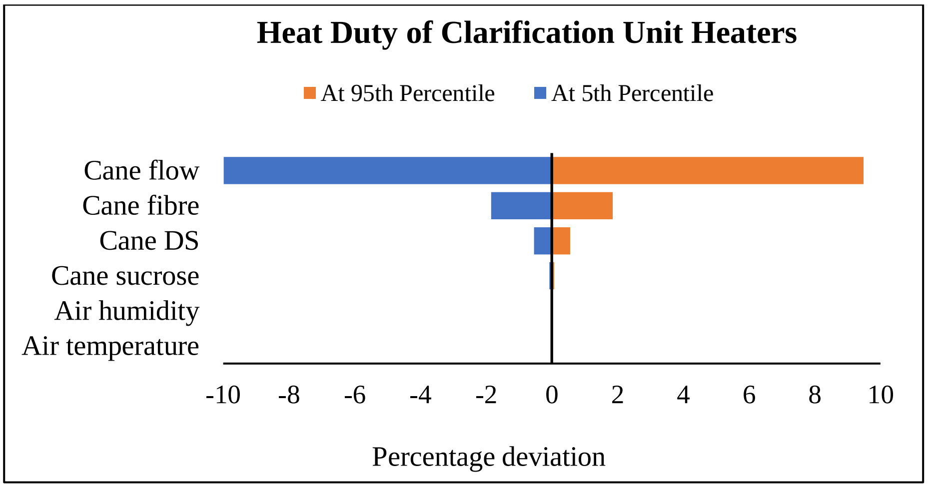

Figure 6-8: Sensitivity analysis plot of the heat duty at the 5th and 95th percentile values of the process disturbances; with the 50th value as the baseline.

The sugarcane flow, fiber, and DS content are the most influential variables in the steam demand of the clarification unit heaters. Air humidity and temperature have no effect, which is expected since there is no link between the sugar drier and the clarification unit from an energy perspective. The DS content represents all the sucrose and non-sucrose material dissolved in the solution. Therefore, in Figure 6-8, the observed difference between the impact caused by the sugarcane DS and sucrose content variations is because of the non-sucrose component. Based on the large difference observed, not only sucrose recovery depends on the sugarcane non-sucrose content [12] but also the energy demands of the clarification heaters.

At high sugarcane non-sucrose content, there is an increase in the impurities and hence mud produced in the clarifier [12]. To minimize the sucrose losses in the mud, wash water addition in the vacuum filter is done relative to the quantity of mud. Increased addition of washing water leads to higher filtrate flows to the MJ tank, thereby, increasing the vapor demands in the heaters. A balance is required between sucrose recovery and energy usage when it comes to water addition, which can be challenging due to the variations in sugar and bagasse prices. Of the three heaters, the primary heater consumes more energy. As an energy improvement measure, some factories return the filtrate to an intermediate tank located after the primary heater to ensure that the increase in filtrate flow does not apply to the primary heating step [12].

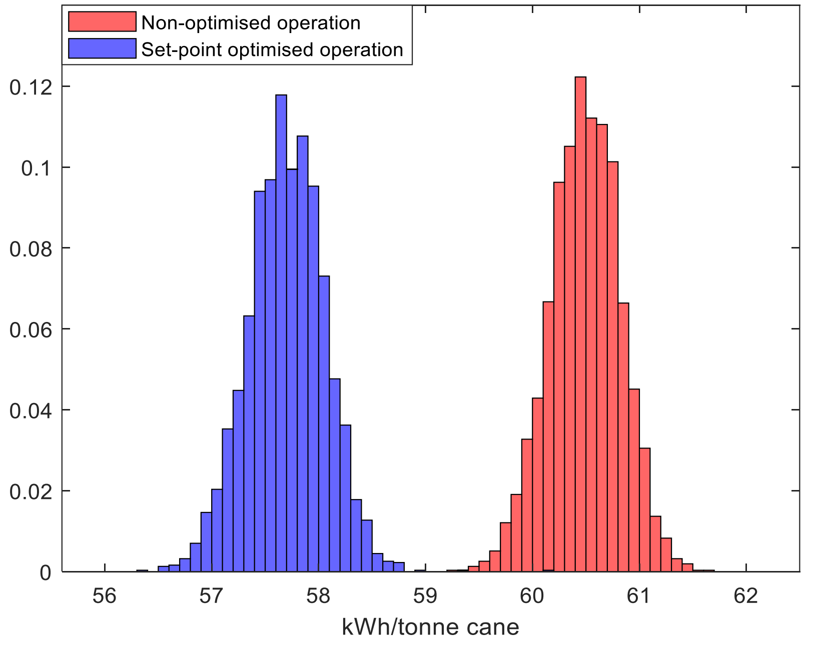

Figure 6-9: Comparison of the steady-state deviation of the clarification unit heat duty for a non-optimized and a set-point optimized operation.

However, the present study results in Figure 6-9 show that for a factory with the mixing tank located before the heaters, the total heat duty of heaters can still be reduced by implementing set-point optimization. With set-point optimization when variations in process disturbances and market prices occur, the heat duty of the clarification heaters are found to mainly lie between 56 and 59 kWh/tonne sugarcane as compared to the observed ranges of 59 and 62 without optimization. By recommending the use of set-point optimization and using the operating net-revenue as a test for optimality, this study provides an explicit and scientifically sound method for determining the balance between energy usage and sugar production improvement.

6.3.2. Evaporation unit

Previous studies have recommended attaining high syrup DS content and lowering massecuite recycling as options for minimizing large deviations in the evaporator unit energy indicator [6]. The present study further shows that by using a set-point optimizer, the energy demand of the evaporator unit can be substantially reduced. This observation is illustrated in Figure 6-10.

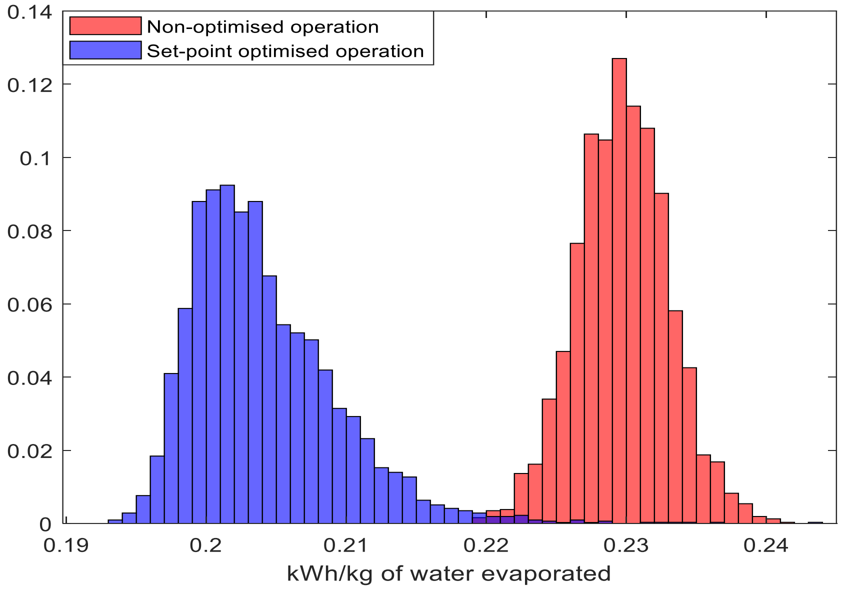

Figure 6-10: Comparison of the evaporator energy indicator for the non-optimized and optimized operation

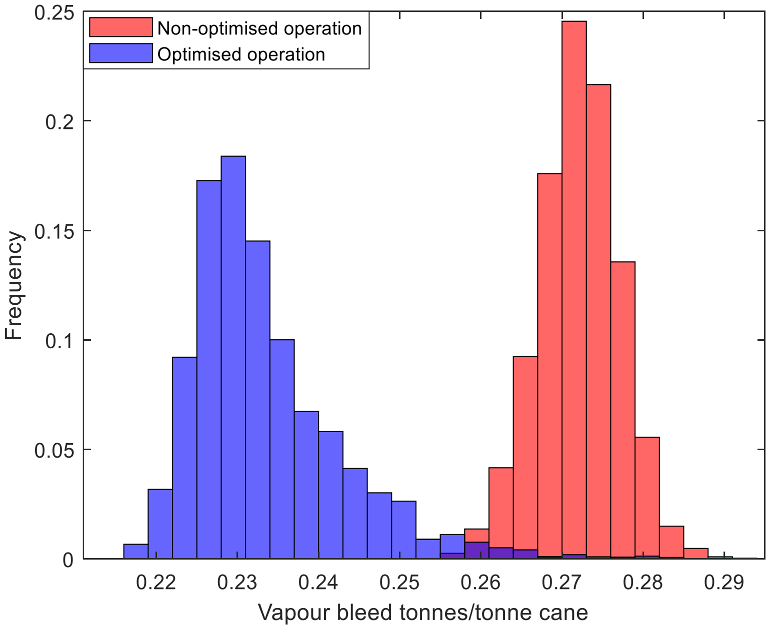

Figure 6-11: Comparison of the total vapor used per tonne sugarcane for the non-optimized and set-point optimized operation

For non-optimized operation, the evaporator energy indicator values are between 0.22 and 0.24 (kWh/ kg of water evaporated), while for the set-point optimized operation they are reduced to between 0.19 and 0.22. Set-point optimization shifted the envelope of operation toward improved evaporator energy demand as seen by the mean value shift to 0.20 (kWh/kg of water evaporated) compared to 0.23 for non-optimized operation. Energy inefficiencies in the extraction, clarification, and crystallization unit influence the steam economy of the evaporator unit through vapor demand [6]. Pinch technology [39] and new evaporator designs [7] have been used in previous studies to reduce the vapor bleed demands. The current study has further contributed to the available studies by illustrating the attainable improvements in vapor demand with set-point optimization when process and market price disturbances occur (Figure 6-11). Based on the mean values for non-optimized and optimized operation, it is observed that set-point optimization leads to an 11 and 14 % reduction in the evaporator unit energy indicator value and total vapor bleed demand, respectively.

6.3.3. Crystallization unit

The exergy analysis of a sugarcane mill by Dogbe et al. [13] found the B and C pans contribute 19% of the irreversibility in the crystallization unit. Achieving high A-massecuite DS content (low A-massecuite recycling) is vital for reducing the feed load on the next pan stages (reducing irreversibility). From an energy view, it lowers the evaporation load and vapor demands in the B and C pans [6]. This present study further shows in Figure 6-12 that total massecuite recycling can be substantially reduced with set-point optimization. For non-optimized operation, massecuite recycling lies between 1.45 and 1.49 while with set-point optimization, the range reduces by 22% to 1.09 and 1.18 m^3/tonne MJ DS content.

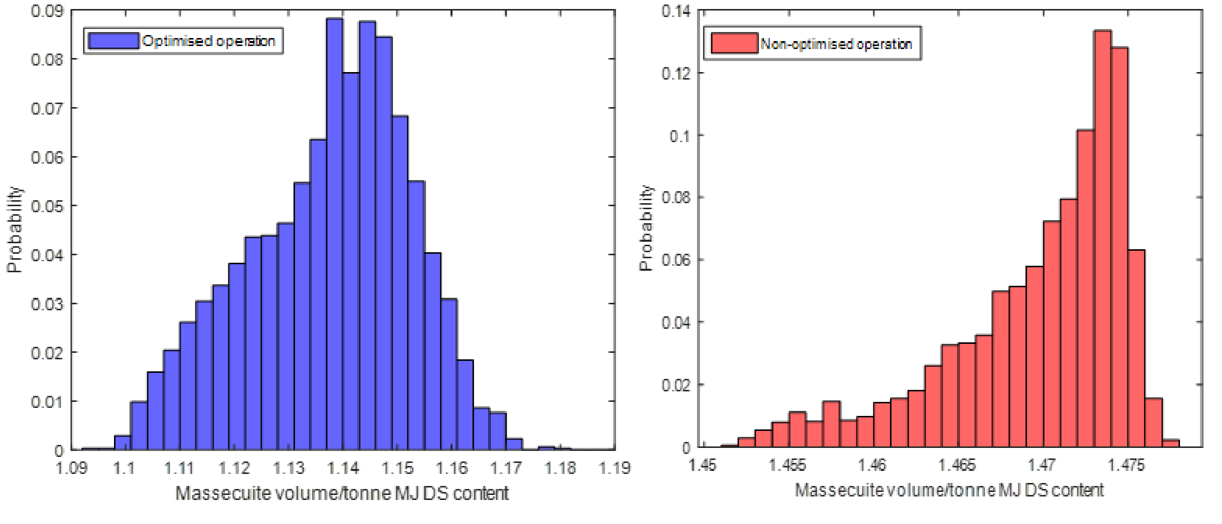

Figure 6-12: Massecuite recycling for optimized and non-optimized operation

6.3.4. Boiler unit

While in chapter 5 the boiler efficiency was shown to be influenced by the bagasse moisture content and flue gas temperature and oxygen content, in the present chapter it is further shown in Figure 6-13 that the variations of the external process disturbances also affect the boiler efficiency. Of all the 6 process disturbances considered in this study, the sugarcane flow and the sugarcane fiber and DS content are shown to have the largest influence on the boiler efficiency. The fact that the sucrose content of sugarcane is shown to have a lower impact compared to the DS content indicates that the non-sucrose component of sugarcane has the largest impact on the boiler efficiency relative to its sucrose component. Hence the non-sucrose component of sugarcane does not only have an impact on sugar recovery but also influences the attainable boiler efficiencies.

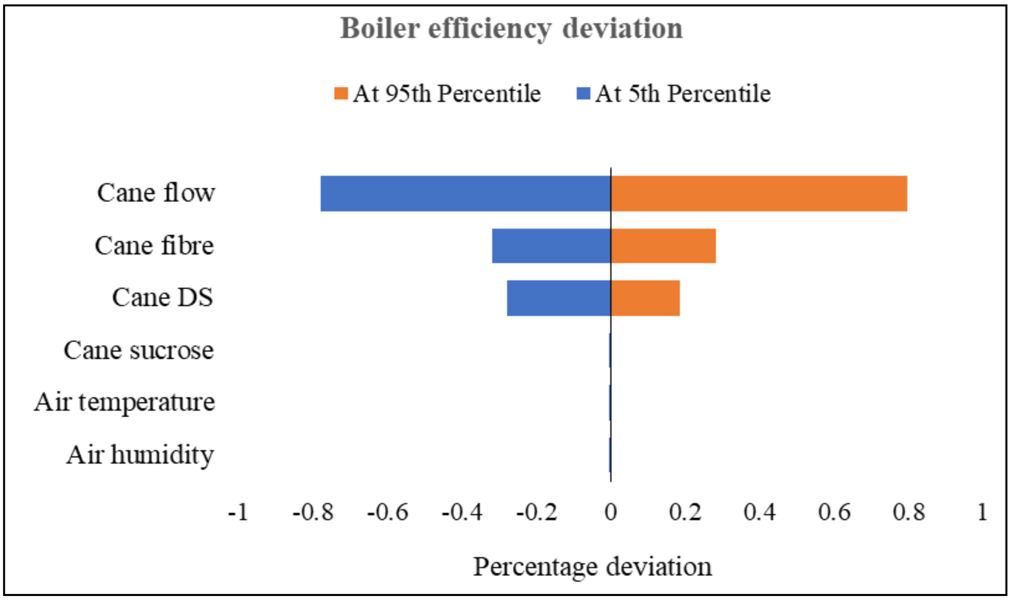

Figure 6-13:Sensitivity analysis plot of the boiler efficiency at the 5th and 95th percentile values of the process disturbances; with the 50th value as the baseline.

The fiber content of sugarcane influences the amount of bagasse available to a factory while the DS content influences the calorific values of bagasse. When the fiber content of sugarcane is high there is an increased likelihood of high sucrose losses to the bagasse stream exiting the dewatering mill. However, with an increase in the DS content of bagasse, there is a corresponding increase in the load of alkali metals to the boiler system [21]. If the alkaline salts condense onto the heating surfaces, they hinder heat transmittance and result in reduced boiler efficiencies Hence the variations in the disturbances result in changes in the available bagasse energy content and variations in the process steam demand which both ultimately lead to load and boiler efficiency fluctuations. From Figure 6-14 the random variations of the external process disturbances and market prices result in boiler efficiency variations between values of 65 and 68.5%. However, with set-point optimization of the sugar production units, the boiler efficiency increased by 0.55% (Figure 6-14) while the HP steam-generating cost is reduced by 0.68% (Figure 6-15). Therefore, in addition to the recommendations of chapter 5 to reduce the bagasse moisture content and the flue gas temperature and oxygen content, the present chapter further shows that the boiler efficiency and HP steam-generating cost can be improved through set-point optimization of the sugar production units. Hence the proposed strategy for set-point optimization is beneficial for not only improving the sugar production units but also reducing bagasse energy wastage in the boiler (utility section).

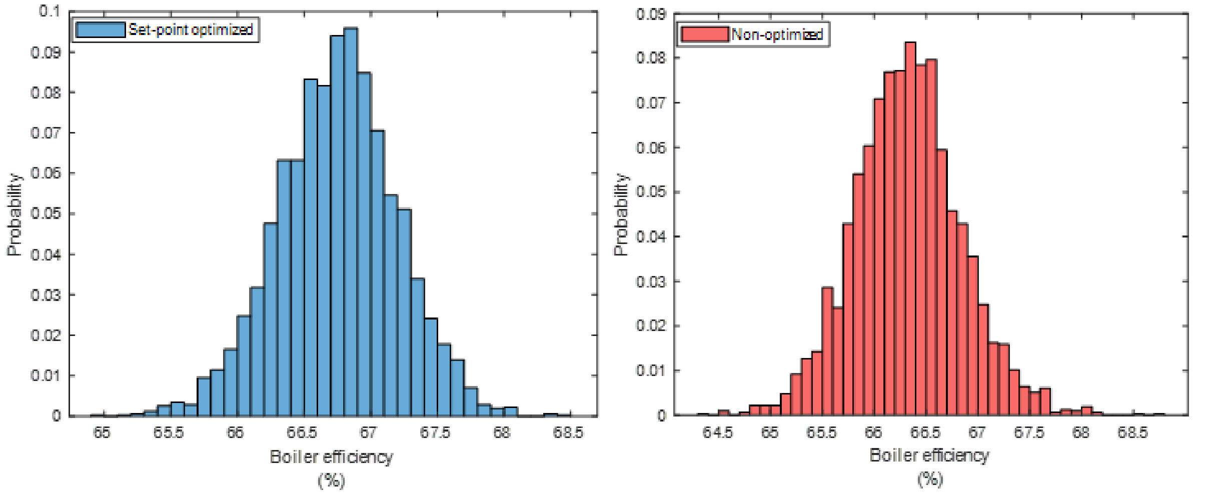

Figure 6-14: Boiler efficiency variation for set-point optimized and non-optimized operation

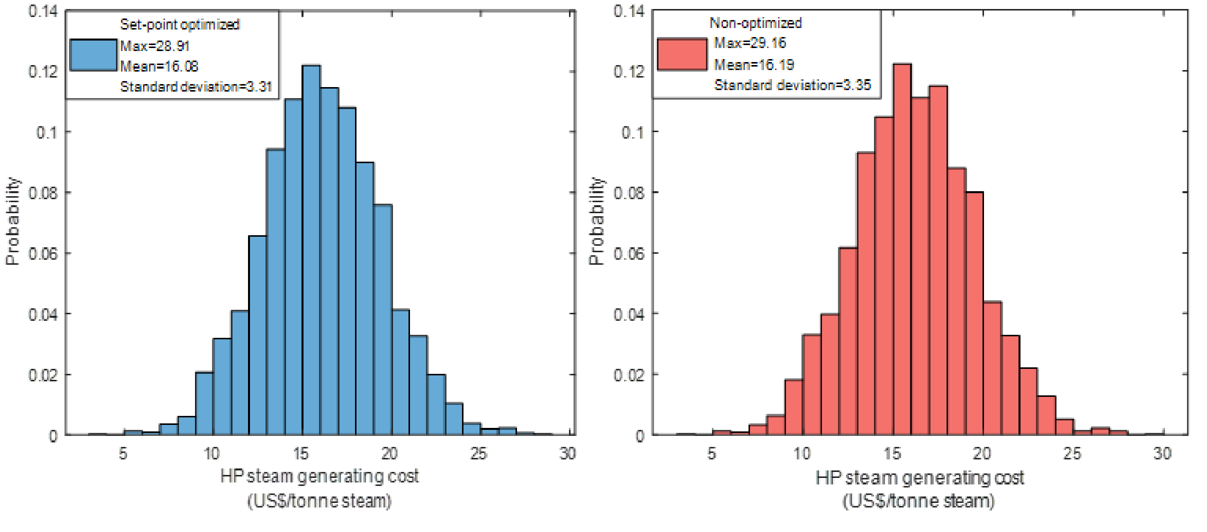

Figure 6-15:Comparison of the HP steam-generating cost for non-optimized and the set-point optimized operation

6.3.5. Overall HP steam consumption

Based on Chapter 4 findings, an increase in A and C massecuite recycling leads to an increase in HP steam used per unit of sugarcane while an increase in C-massecuite recycling lowers the HP steam used per unit of sugar. This contradiction was attributed to the failure of the HP steam used per tonne of sugarcane index to capture the sucrose recovery losses caused by reduced C-massecuite recycling [6]. The authors recommended the use of both indicators to balance between energy usage and sugar production improvement [6]. The present study (Figure 6-16 and Figure 6-17) shows that the overall HP steam usage in terms of both sugarcane and sugar produced can be reduced with set-point optimization.

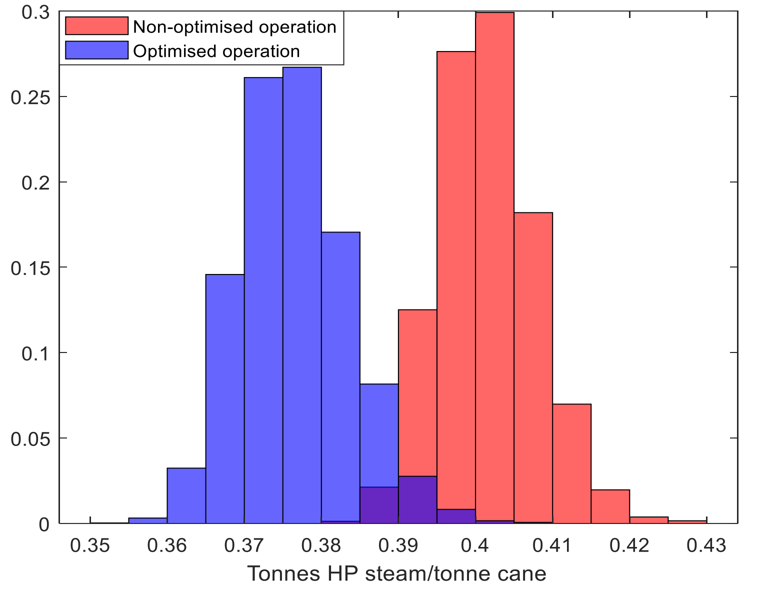

Figure 6-16: Comparison of the tonnes of HP steam used per tonne sugarcane

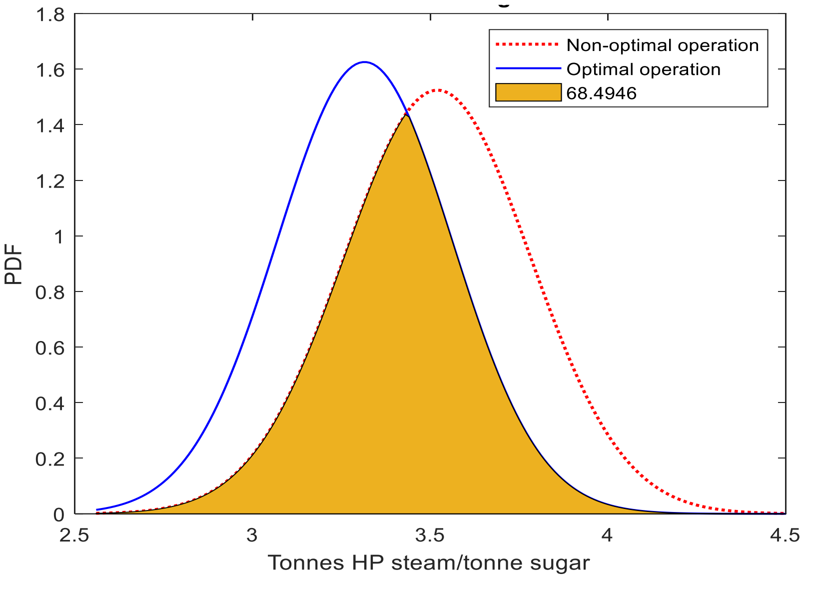

Figure 6-17: Non-optimized and optimized distributions of the tonnes of HP steam used per tonne sugar

With the occurrence of process and market price disturbances, the tonnes of HP steam used per tonne sugarcane lies between 0.38 and 0.43 without optimization and between 0.35 and 0.40 with set-point optimization. Although the overlap between the non-optimal and optimal HP steam used per tonne sugar values is significantly high (68%), there is still a shift in the mean value from 3.52 tonnes HP steam/tonne sugar to 3.32 with set-point optimization. This indicates that with set-point optimization a balance can be found such that the overall improvement on HP steam usage is attained regardless of whether it is evaluated in terms of sugarcane or sugar.

6.3.6. Net revenue and products

Figure 6-18 is a Tornado plot that shows the effect of process and market price disturbances on the net revenue of a sugarcane factory. The market prices have the most significant effect on the net-revenue relative to the process disturbances.

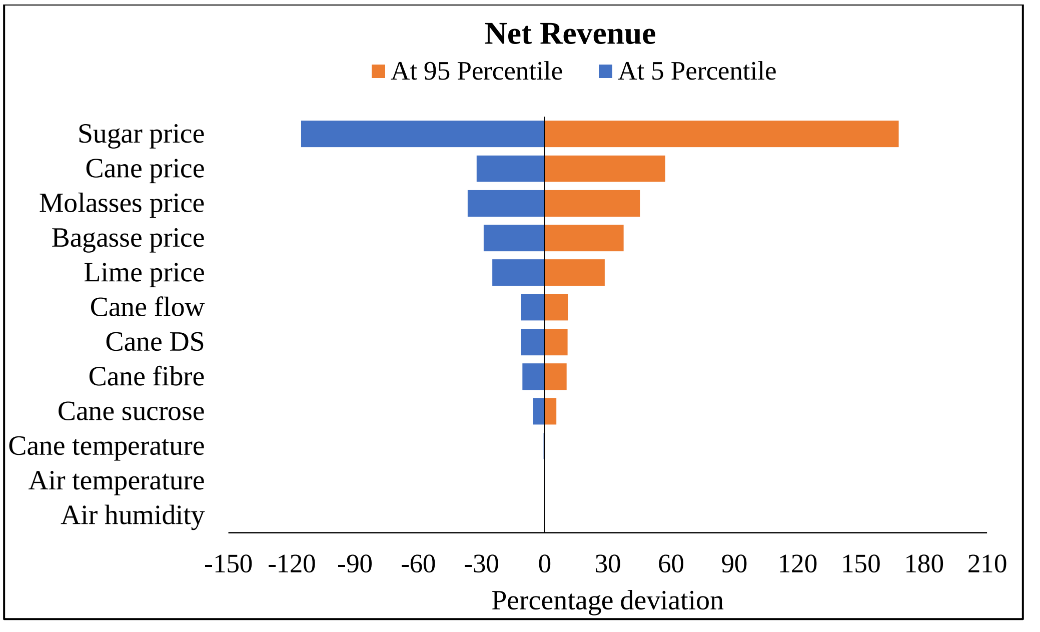

Figure 6-18: Tornado plot for net revenue at 5th and 95th percentile values of disturbance.

With set-point optimization, the mean value for export surplus bagasse and molasses was increased by 8.5% and 1.54 % with an acceptable 0.43% reduction in the mean value of produced sugar. Despite the sugar price being the most influential variable, this was all achieved while improving the mean net revenue by 2.4%. This shows that the optimizer can find the global optimal point at which the loss in surplus bagasse revenue due to excess energy use (to minimize sucrose loss) no longer justifies the corresponding revenue gain from the produced sugar. The increase in available surplus bagasse coupled with the 6.23% reduction in HP steam used per tonne sugarcane makes it possible for a relatively large bio-refinery to be annexed to a set-point optimized sugarcane factory. Therefore, the strategy used for set-point optimization in this study does not only optimize the sugar mill operations but can increase the capacity of bio-refineries that use either bagasse or molasses as feedstock.

6.4. Industrial operational recommendations

6.4.1. Robust and resilient optimal CV set-points

For a feedback optimizing control structure, Morari et al. [40] suggest the use of CVs which when held at their constant set-points leads automatically to the optimal adjustment of the manipulated variables and with it, maximum factory revenue. In the present study, out of the 14 CVs used in the set-point optimizer, the following 9 CVs have optimal set-points that are robust and resilient to the random variations in the process disturbances and market prices:

i. Press water after the heater (65°C).
ii. MJ after the primary, secondary, and tertiary heaters (85,97 and 102 °C, respectively).
iii. A- massecuite DS content (94%)
iv. B- massecuite temperature (61°C).
v. C- massecuite DS content (93%).
vi. C- massecuite temperature (61°C).
vii. Re-melt DS content (80%).

Thus, when these CVs are held constant at their steady-state optimal set-points there is no need to reoptimize for them when process and market price disturbances occur. High C massecuite DS content is often urged in literature studies [6] for increasing the sugar yields and minimizing the sucrose losses in the C-molasses stream exiting the factory. This operation strategy leads to excess energy usage to recover sucrose from molasses. Of all the scenarios of process disturbances and market price variations, no instance favors the extra energy usage for recovery of sucrose from molasses such that the steady-state optimal value of the C-massecuite DS content is increased above 93%. Therefore, contradictory to the previous studies, the present study suggests a lower value for the C-massecuite DS content is preferred for synthesizing feedback optimizing control structure for maximum factory revenue.

6.4.2. Non-robust and optimal CV set-points

The following CVs were observed to have optimal set-points that are sensitive to the variations in the process and market prices disturbances and require frequent re-computing:

i. Juice after the preheater (110-116°C)
ii. Final syrup DS content (60-72%)
iii. A-massecuite temperature (61-74°C)
iv. B-massecuite DS content (92-96%)
v. Re-melt temperature (60-80°C).

Considering the significance of the syrup DS content and the A-pan operation, predictive models for the optimal set-point value of syrup DS content (Equation (6-5)) and A-massecuite temperature (Equation (6-6)) based on the significant disturbances were developed. About 75% of the randomized values of the process and market price disturbances and the corresponding optimal set-point values for syrup DS content and A-massecuite temperature were used to train and cross-validate the model, while the remainder was used to test the model. Only the disturbances with a variable importance projection (VIP) greater than 1 were considered for the predictive models [41]. Partial least squares regression was used as it can handle data with many and high correlated independent variables [41]. The predictive models of syrup DS content and A-massecuite temperatures have R^2 values of 0.77 and 0.89, respectively, which shows a good fit between the observed and predicted optimal set-points. High sugarcane DS content, molasses price, and surplus bagasse price prompt the need for higher optimal set-points for the syrup DS content to ensure maximum revenue. High sugarcane flow and molasses prices are observed to favor the use of higher A-massecuite temperatures, while high sugar and surplus bagasse prices favor lower temperatures. Achieving the maximum attainable syrup DS content is often suggested in the literature [12] but from the present study results, this has been shown to depend on the DS content of sugarcane and the prices of molasses and bagasse.

$$\begin{aligned}\text{Optimal syrup DS content (\%)} \\ &= 133.78 - 0.60\mathrm{F_{CANE}} + 2.58\,\mathrm{x_{CANE\ DS}} - 0.53\mathrm{P_{CANE}} - 0.35\mathrm{P_{SUGAR}} \\ &+ 1.07\,\mathrm{P_{MOLASSES}} + 1.53\mathrm{P_{SURPLUS\ BAGASSE}}\end{aligned} \tag{6-5}$$

$$\begin{aligned}\text{Optimal A massecuite temperature (°C)} \\ &= 66.66 + 0.022\mathrm{F_{CANE}} - 0.24\mathrm{P_{SUGAR}} + 0.78\,\mathrm{P_{MOLASSES}} \\ &- 0.27\mathrm{P_{SURPLUS\ BAGASSE}}\end{aligned} \tag{6-6}$$

To avoid frequent re-optimization when disturbances occur, Skogestad [42] introduced a concept known as "self-optimizing control". In self-optimizing control, instead of trying to achieve the best possible economic performance, a balance is made between profitability and the simplicity of not having to re-optimize when disturbances occur. Self-optimizing control involves finding optimal measurements for the CVs such that when held constant at their optimal set-points, minimal economic loss is attained without the need to re-optimize when disturbances occur. The revenue loss is due to the combined effect of the disturbances and the CV measurement error in the feedback controllers attempt to maintain a constant set-point policy [42]. Precise measurements allow the operation of a factory closer to constraints that harbor more revenue. Therefore, there is scope for future work focused on finding optimal measurements for the CVs considered in this work such that the frequency of set-point optimization in the sugarcane factory is further reduced or even eliminated.

6.5. Conclusions

The study presented a strategy for implementing a plant-wide steady-state optimal operation policy for sugarcane mills when process and market price disturbances occur. The strategy uses set-point optimization to find the optimal set-points for 14 CVs such that maximum profitability is attained despite the random and unavoidable variations of the process and market price disturbances. Based on the historical data of the process and market price disturbances, their probability distribution functions were generated to reflect their likelihood of occurrence in a sugarcane mill. The Monte

Carlo approach was used to randomly take samples of the process and market price disturbances and simulate them into the sugarcane mill and financial models, respectively. To assign an economic value to plant-wide control objectives, the financial model defines the net-revenue as the difference between the product revenues and the raw materials expenditure.

With set-point optimization, the mean value for surplus bagasse increased by 8.5% with a satisfactory 0.43% reduction in the mean value of produced sugar. Despite the sugar price being the most influential variable, this was achieved while improving the mean net revenue by 2.4%. Considering, the global move to bio-based products and the key-role the sugar industry can play in the commercialization of bio-refineries, the increase in available surplus bagasse makes it possible for a relatively large bio-refinery to be annexed to a set-point optimized sugarcane factory. Therefore, the strategy used in this study for set-point optimization does not only optimize the sugar mill operations but can increase the capacity of bio-refineries that use bagasse as feedstock. Energy indicators like massecuite recycling and steam usage retained improvements of 23 and 6%, respectively. Nine CVs were observed to have optimal set-points that are robust and resilient to variations in the process and market price disturbances. For steady-state feedback optimizing control structure when disturbances occur, the present study suggests holding these 9 CVs constant at their optimal values while set-point optimization is done for the remaining 5 CVs.

Acknowledgments

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Chapter 7

7. Optimal Sensor Network Design for A Typical Sugarcane Mill Using Self-Optimizing Control and Genetic Algorithms

This chapter is planned for submission to the "Journal of Process Control"

https://www.journals.elsevier.com/journal-of-process-control

The objective of the dissertation in this chapter and the summary of findings

Plant-wide selection of measured variables is important for effective process monitoring and automated control. This is based on the realization that the benefits attained from implementing the feedback control law largely depends on the accuracy and precision of the measured variables. The review of the literature and the reported industry needs revealed a lack of adequate instrumentation and precise measurements in sugarcane mills. Furthermore, an attempt made by the author and industry personnel to calculate the energy indicators from Chapter 4 in South African sugarcane mills was unsuccessful due to the inadequacy of measurements. This revelation motivated the formulation of objective 4, which seeks to find optimal CV measurements by using the self-optimizing control concept and genetic algorithms. In self-optimizing control, optimal measurements are selected as CVs such that minimal revenue loss is incurred without re-optimization when disturbances occur. The selection of 41 optimal measurements for use as self-optimizing CVs was considered to enable independent control, based on 41 remaining degrees of freedom (manipulated variables). Optimality is defined as minimizing the total cost of purchasing the sensors and the steady-state revenue loss for facilitating self-optimizing control, thus constant set-point policy. While other sensor-related costs like installation and maintenance costs can be incorporated in sensor network design, in the present study only the sensor purchasing costs normalized based on the life span of the respective sensor are considered. For the typical sugarcane mill that processes 250 tonnes of sugarcane per hour, the optimal steady-state net-revenue was found to be US$3652.81/hr. For facilitating self-optimizing control, the economically optimal sensor placement found in the present study had an average revenue loss of US$61.93/hr as compared to the typical industry sensor placement, which had an average loss of US$157.72/hr. These losses correspond to a total instrumentation purchasing cost of 4.41 and 4.30 US$/hr, respectively. The substantial reduction in revenue loss for the optimal sensor placement is accredited to 19 CVs that the study methods managed to find more precise measurements for, as compared to the base case sensor network. This is the first study to use the self-optimizing control concept for optimal sensor placement in a sugarcane mill.

SOM refers to the supplementary material for this chapter, which is found in Appendix C.

Declaration by the candidate

With regards to Chapter 7, the nature and scope of my contribution were as follows:

Nature of contribution	The extent of contribution (%)
Project and scope definition, analysis of data, interpretation of results, and writing of chapter	80

The following co-authors have contributed to Chapter 7.

Name	e-mail address	Nature of contribution	Extent of contribution (%)
T.M. Louw	tmlouw@sun.ac.za	Assisted in the development of the chapter's scope. Provided review and proofreading of the chapter.	10
L.Auret	lauret@sun.ac.za	Assisted in the development of the chapter's scope. Provided review and proofreading of the chapter.	5
M.A. Mandegari	mandegari@sun.ac.za	Assisted in the development of the chapter's scope. Provided review and proofreading of the chapter.	5

Signature of candidate:

Date: March 2021

Declaration by co-authors:

The undersigned hereby confirm that

1. the declaration above accurately reflects the nature and extent of the contributions of the candidate and the co-authors to Chapter 7

2. no other authors contributed to Chapter 7 besides those specified above, and

3. potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 7 of this dissertation.

Signature	**Institutional affiliation**	**Date**
	Stellenbosch University	
	Stellenbosch University	
	Stellenbosch University	
	Stellenbosch University	
	Stellenbosch University	

Optimal sensor network design for a typical sugarcane mill using self-optimizing control and genetic algorithms

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Abstract

The concept of self-optimizing control is used for the simultaneous selection of 41 optimal linear controlled variables (CVs) and their optimal sensor placements for use as constant CVs, such that minimal revenue loss is achieved without re-optimizing when disturbances occur. A case study of a typical sugarcane factory that processes 250 tonnes of sugarcane per hour is considered. Optimality is defined as maximizing the sugarcane factory net-revenue by minimizing the total cost of purchasing the sensors and the revenue loss resulting from the effect of the disturbances and measurement errors on the controllers' attempt to implement a constant set-point policy. The optimal steady-state net-revenue was found to be US$3652.81/hr. The economically optimal sensor placement found in the present study has an average revenue loss of US$61.93/hr as compared to the base case sensor placement which has a loss of US$157.72/hr. These losses correspond to a total instrumentation purchasing cost of 4.41 and 4.30 US$/hr, respectively. The substantial reduction in revenue loss for the optimal sensor placement is accredited to 19 CVs which have more precise measurements as compared to the base case network. The cost of purchasing more precise sensors for these 19 CVs is US$2.23/hr.

Keywords: Self-optimizing control; Sugarcane mill; Sensor network; Genetic algorithms; Monte Carlo; Set-point optimization

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7.1. Introduction

The selection of measured variables is a crucial task for effective monitoring, control, and safe operation of a chemical process [1,2]. However, because of the nature of the process and the high cost of measuring instruments, only a subset of the variables can be measured [3–6]. Strategies for sensor selection are often formulated to address a specified process activity, for example, process monitoring or quality control. From a control viewpoint, Skogestad [7] introduced the concept of self-optimizing for addressing the problem of selecting measurements for CVs while reducing or even eliminating the need for real-time optimization (RTO). Often a real-time optimizer or a model-based controller such as economic model predictive control is proposed for optimal control [8]. Both approaches use a process model together with measurements from the process to determine the optimal operating conditions by solving the optimization problem online [9]. However, even with today's computing power, this is often computationally expensive for a factory with high disturbance frequencies [9] and challenging for a factory with no online measurements for disturbances. Besides, model-based controllers may be sensitive to unmodelled disturbances, and structural mismatches [9]. In self-optimizing control, optimal linear measurements are selected as CVs such that when held at constant set-points without RTO when disturbances occur, the revenue loss is still minimized [7,9]. This systematic selection of measured CVs can potentially eliminate the need for an expensive online optimizer to re-optimize when disturbances occur or at least the re-optimization may be performed less frequently [9].

However, in the attempt to simplify the plant-wide control of a factory through the constant set-point policy a loss, $\mathrm{L} = \left(\mathrm{J_{opt}}(\mathrm{d}) - \mathrm{J}(\mathrm{d},\mathrm{n})\right)$ occurs [7]. Thus, the loss in revenue is defined as the difference between the truly optimal value $\mathrm{J_{opt}}(\mathrm{d})$ of the objective function when RTO is done and the value $\mathrm{J}(\mathrm{d},\mathrm{n})$ when constant set-points are used. Disturbances (d) results in the steady-state value deviation of the CVs and the measurement errors (n) lead to differences between the actual CV value and the desired, constant set-point. Therefore, the loss in revenue, L is due to the combined effect of the disturbances (d) and measurement errors (n) on the feedback control systems that attempt to achieve a constant set-point policy. Based on fixed measurements (or sensors), previous studies have used the concept of self-optimizing control to find linear combinations of measurements that can be used as constant CVs [7,10–12]. There are no known studies that have used this concept for sensor selection, such that different sensors are specified for the measurements, thereby allowing for the simultaneous optimal selection of linear CVs and their corresponding optimal measurement error specifications.

Therefore, the aim of this is to present a strategy for simultaneously finding an optimal linear combination of CVs and their optimal corresponding sensor precisions that can be used for facilitating self-optimizing control. The sugarcane industry is responsible for much of the global sugar production and the significant contribution to the gross national products of countries like China, Thailand, and South Africa [13]. Like any other industry, the sugarcane mills face intense pressure to improve their production and energy efficiency to remain economically viable. However, frequent disturbance variations, inadequate instrumentation, imprecise sensors, and budget constraints are reported as some of the barriers to effective process control and improved energy efficiency in sugarcane mills [14–16].

Hence the proposed strategy for optimal sensor placement is illustrated for a sugarcane mill that consists of juice extraction, clarification, evaporation, crystallization operations as well as utility systems (boiler, cooling tower, and turbogenerator). Industrial cost constraints further limit the number and precision of sensors that can be purchased. In this regard, optimality for sensor placement is defined as maximizing the net-revenue by simultaneously minimizing the loss in revenue, L, and the required cost of instrumentation. As the number of possible linear measurement combinations increases with process dimensions, an exhaustive search can be computationally intractable [6], hence methods like the branch and bound [18], mixed-integer linear programming techniques [3], and genetic algorithms (GAs) [18] have been used in literature for optimal sensor placement. For the present study, GAs is used as they can handle integer optimization problems for large systems.

7.2. Self-optimizing control theory

Figure 7-1 is an illustration of the interaction between the local optimization layer and the feedback control structure. Based on the process measurements (y), a set of measurements (c) are used as CVs. The optimization layer computes the optimal set-points that the control layer then attempts to implement. The factory economics is assumed to be characterized by a scalar objective function, $\mathrm{J(u,d)}$, where u and d are the manipulated and disturbance variables, respectively. The general optimal operation policy entails updating u according to the d values using an online optimizer to obtain the optimal objective function value, $\mathrm{J_{opt}(d)}$. To achieve truly optimal operation, measurements for all disturbances must be available and all the resulting dynamic optimization problems must be solved online using a very accurate process model [7].

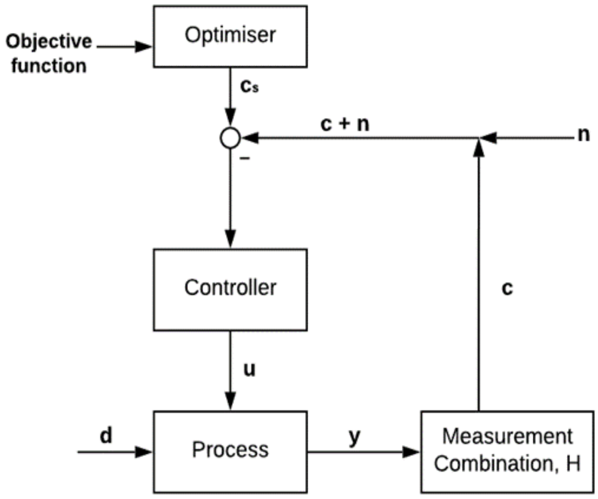

Figure 7-1:Feedback control structure with a steady-state optimization layer where cs, c, n, u, d, and y denote the set-points, linear measurement combination, measurement error, manipulated variables, disturbances, and process output variables.

Hence an alternative and simpler strategy is the use of a feedback controller that updates u to hold the linear combination of the measured CVs (c) at constant set-points when disturbances occur, without RTO [7]. While avoiding RTO, this constant-set-point policy does lead to a revenue loss, L as compared to the truly optimal case where RTO is done with the ingress of d.

$$\mathrm{L(d)} = \left(\mathrm{J_{opt}(d)} - \mathrm{J(d,n)}\right) \tag{7-1}$$

The revenue loss, L is mainly caused by two errors:

i. Set-point error due to disturbances- A closed-loop implementation is considered that attempts to keep the selected linear combination of measured CVs at constant set-points without dynamic set-point re-optimization. Hence the resulting difference between the optimal set-points under the considered disturbances and the constant set-point (c_s) leads to a set-point error.
ii. Implementation error (n) - For a closed-loop system the assumption of zero steady-state control error is satisfied if an integral controller is used, so the only implementation error is due to the measurement errors [7]. The measurement error associated with each measured CV leads to differences between the true CV value and c_s.

Therefore, to select the best linear combination of CV measurements for self-optimizing control from the candidate measurements of the process output variables (y), the following requirements must be satisfied [12]:

i. The adjustments of u with d must result in a large value change of the CVs so that the transfer function gain from u to c is large.
ii. The CVs' constant set-points must be insensitive to d to minimize the set-point error.
iii. Precise CV measurements must exist to minimize the implementation error.

7.2.1. Linearised models and computation of the H matrix

The relationship between the output process variables (y) and the process inputs u and d are $\mathrm{y} = \mathrm{f_y(u, d)}$. For small deviations around the nominal disturbance values, the linearized relationship between the unconstrained degrees of freedom u and y is:

$$\Delta \mathrm{y} = \mathrm{G^y} \triangle \mathrm{u} + \mathrm{G_d^y} \triangle \mathrm{d} \tag{7-2}$$

Where $\triangle \mathrm{u} = \mathrm{u} - \mathrm{u}^*$, $\triangle \mathrm{d} = \mathrm{d} - \mathrm{d}^*$, $\mathrm{G^y} = \left(\frac{\partial \mathrm{f_c}}{\partial \mathrm{u}}\right)^{*\mathrm{T}}$ and $\mathrm{G_d^y} = \left(\frac{\partial \mathrm{f_c}}{\partial \mathrm{d}}\right)^{*\mathrm{T}}$. The asterisk $(*)$ denotes nominal operation while the superscript T denotes the transpose of the matrix. Similarly, the linearized model of the relationship, $\mathrm{c} = \mathrm{f_c(u, d)}$ between the unconstrained degrees of freedom u and the CVs (c) is:

$$\Delta c = G^c \triangle u + G_d^c \triangle d \tag{7-3}$$

Where, $\triangle c = c - c^*$, $G^c = \left(\frac{\partial f_c}{\partial u}\right)^{*T}$ and $G_d^c = \left(\frac{\partial f_c}{\partial d}\right)^{*T}$. To select measurements to use as self-optimizing control CVs, a search through the potential process output variables measurements (y) is done to find the best linear combination of CV measurements, (c=Hy), which, when used as constant CVs lead to minimal revenue loss, L [19]. If any variable can be measured by more than one sensor it must be repeated in the vector y of the process measurements, hence it is at this stage that the sensor placement aspect is introduced in the self-optimizing concept.

From the process output variables (y), the number of variables that can be independently controlled ($\mathrm{N_c}$) is equal to the number of the independently manipulated variables ($\mathrm{N_u}$). However, in most cases, the number of the output variables ($\mathrm{N_y}$) is larger than the manipulated variables ($\mathrm{N_u}$). This gives rise to the problem of selecting the non-square matrix, H such that the transfer function G^c from u to c is square [20]. As shown in Equation (7-4), for a given set of candidate output variables measurements (y), the H matrix is free to choose a linear combination of measurements (c) represented by Hy to facilitate self-optimizing control.

$$\Delta c = H\Delta y \tag{7-4}$$

By introducing, $F = \frac{\Delta y^{opt}}{\Delta d} = -\left(G^y {J_{uu}}^{-1} J_{ud} - G_d^y\right)$ as the sensitivity of the optimal y values to small variations in the disturbances, Equation (7-4) can be rearranged to be:

$$\Delta c^{opt} = H\Delta y^{opt} = HF\Delta d \tag{7-5}$$

Therefore, from a linear view, the problem of selecting the best linear measurements combination (c) for use as constant CVs for self-optimizing control, entails finding the optimal combination matrix H. Halvorsen et al. [10] proposed the choice of the optimum measurement combination matrix H, based on the exact non-linear formulation of the self-optimizing control problem. However, for high-dimensional and non-convex optimization problems, this formulation is tedious and can converge to a local optimum point [7]. Alstad et al. [19] derived an explicit expression for optimal H for the case where the objective is to minimize the loss, due to the combined effect of the disturbances and measurement errors on the controllers attempts to implement the constant set-point policy as:

$$H^T = \left(\tilde{F}\tilde{F}^T\right)^{-1} G^y \left({G^y}^T \left(\tilde{F}\tilde{F}^T\right)^{-1} G^y\right)^{-1} \sqrt{J_{uu}} \tag{7-6}$$

Where, the symbol, $\tilde{F}$ is used to denote $[FW_d \;\; W_n^y]$ while W_d and W_n^y are the diagonal matrices that contain the magnitudes of the d and n associated with the candidate measurements (y), respectively. The second partial derivative J_{uu} is obtained from the second-order Taylor series expansion of the cost function $J(u, d)$ around the optimal operating point $(u^{opt}(d), d)$ such that:

$$J(u, d) = J + (J_u \; J_d)^T \left(\frac{\Delta u^{opt}(d)}{\Delta d}\right) + \frac{1}{2}\left(\frac{\Delta u^{opt}(d)}{\Delta d}\right)^T \mathcal{H}^* \left(\frac{\Delta u^{opt}(d)}{\Delta d}\right) \tag{7-7}$$

Where $J = J(u^{opt}(d), d)$, $J_u = \frac{\partial J}{\partial u}$, $J_d = \frac{\partial J}{\partial d}$, $\mathcal{H}^* = \begin{bmatrix} J_{uu} & J_{ud} \\ J_{du} & J_{dd} \end{bmatrix}$, $J_{uu} = \frac{\partial^2 J}{\partial^2 u}$, $J_{ud} = \frac{\partial^2 J}{\partial u \, \partial d}$ and $J_{dd} = \frac{\partial^2 J}{\partial^2 d}$. For a well-defined optimization problem, J_{uu} must be positive definite to guarantee the existence of the square root of J_{uu}. In the case of a non-positive definite, J_{uu}, Silva et al. [17] propose the use of a modified Cholesky factorization to slightly adjust it to a positive-definite matrix. The explicit expression for the optimal H matrix in Equation (7-6) is used in this present study and a detailed derivation for this expression is provided in Alstad et al. [19].

7.2.2. Exact loss computation

The evaluation of the loss for a non-linear process is challenging [12]. Hence to quickly pre-screen the alternatives, local methods like the minimum singular value rule [11] and exact local methods for worst-case loss and the average loss minimization are used [5,13]. When compared to exact local methods, the minimum singular value rule tends to perform poorly for ill-conditioned plants [21] and multivariable systems [12]. Halvorsen et al. [12] derived the exact local expression (following a second-order Taylor series expansion of the loss function L) for loss minimization as:

$$L_{ave} = \frac{1}{6(n_y + n_d)} \|M\|_F^{\ 2} \tag{7-8}$$

Where,

$$M = [M_d \quad M_n] \tag{7-9}$$

$$M_d = \sqrt{J_{uu}}\left(J_{uu}^{\ -1} J_{ud} - (HG^y)^{-1} HG_d^y\right) W_d \tag{7-10}$$

$$M_n = \sqrt{J_{uu}}\,(HG^y)^{-1}\, W_n^y \tag{7-11}$$

The loss due to disturbances and measurement errors is introduced through M_d and M_n. The dependency of the loss variables M_d and M_n on the matrix, H is introduced through Equations (7-10) and (7-11). The notation $\|.\|_F$ represents the Frobenius norm of the matrix M. The loss relies on the sum of the squares of all the singular values (inclusive of the largest singular value) of the matrix. The worst-case H matrix minimizes the largest singular value but does not necessarily minimize the contribution of the smaller singular values toward the average loss [10]. In this regard, it can be argued that the H matrix that minimizes the average loss should also minimize the worst-case loss [10]. Furthermore, the worst-case loss tends to be conservative as the extreme values of the disturbances might be rarely experienced in actual factory operation [10]. For these reasons, the average loss is deemed more realistic and is used in this present study as represented in Equation (7-8).

7.2.3. Optimal sensor placement based on the self-optimizing control

With an increase in the number of measurement combinations for larger processes, an exhaustive search for optimal sensor placement can be computationally intractable. Therefore, an efficient method is required to find the optimal sensor placements. Tree search procedures [2], mixed-integer linear programming techniques [3], and genetic algorithms (GAs) [2,22,23] have been used in literature for optimal sensor placement. For the present study, GAs is used as they can handle integer optimization problems for large systems. The GAs is a population-based searching algorithm that uses the evolution idea of survival of fittest to search [24,25]. Figure 7-2 shows an illustration of the proposed strategy in the present study for selecting optimal linear CVs and their corresponding sensor specification.

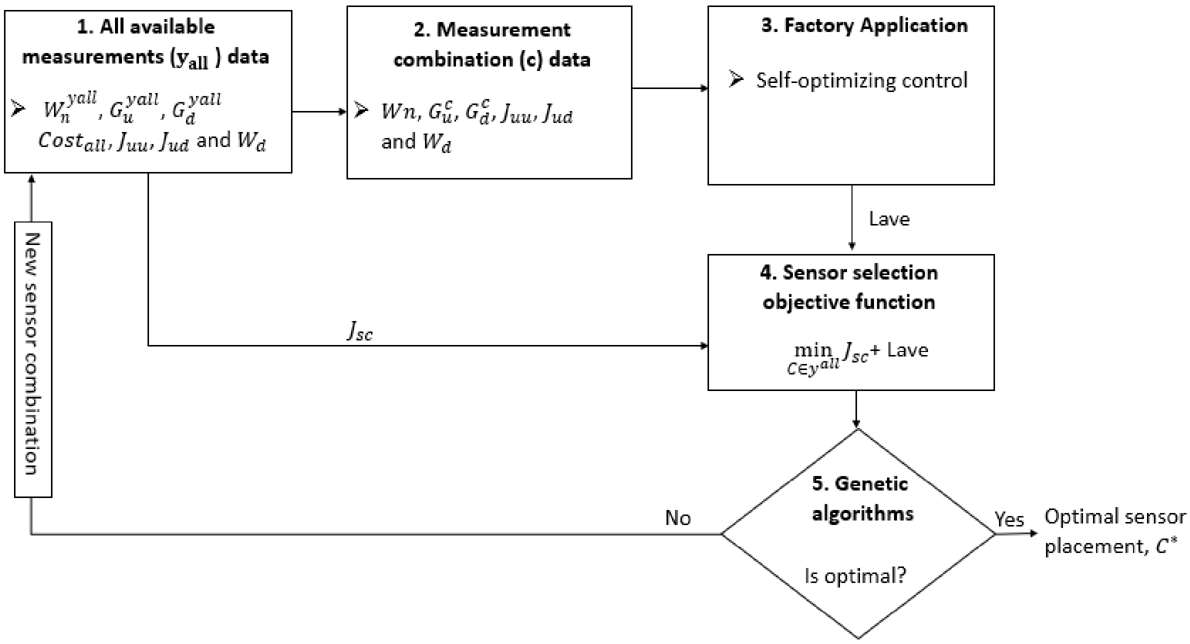

Figure 7-2: Optimal sensor placement strategy based on self-optimizing control

If a variable can be measured with more than one sensor, it should be repeated in the vector y, which represents the measurable process output variables. Hence if for each candidate measurement $N_{sensors}$ alternative candidate sensors are chosen; the total available measurements (sensors) are $y_{all} = N_{sensors} \times y$. From the allocated sensor locations in the sensor combination (chromosome), the corresponding linear combination of CVs (c), the sensor errors (W_n^c), G^c and G_d^c are applied for self-optimizing control together with W_d and the Hessian matrices, J_{uu} and J_{ud}. It is worth noting that W_d and the second partial derivatives, J_{uu} and J_{ud} do not change with sensor location. At this stage, the self-optimizing control capabilities of the selected sensor placement are tested based on the computation of the H matrix followed by the computation of the loss, L_{ave} due to the disturbances effect on the linear combination of CVs (c) and the impact of the allocated sensors measuring errors. The total cost of selected CVs sensors is represented by J_{sc}. The optimal sensor placement (C^*) is, therefore, finally determined using J_{sc} and L_{ave} with the assistance of tools like the Pareto front or by combining them in a common weighted criterion $J_T = (1-k)J_{sc}+kL_{ave})$, where k = 0.5 if J_{sc} and L_{ave} are evaluated in the same financial units. Therefore, for the latter case the optimal sensor placement is formulated as:

$$C^* = \min_{C \in y^{all}} (J_{sc} + L_{ave}) \tag{7-12}$$

If the solution, C^* cannot be obtained analytically from the minimization of Equation (7-12), an iterative procedure is used and a new sensor combination (chromosome) is selected. Reproduction and crossover are important genetic operators used to produce a new chromosome (offspring) [24,25]. As several generations are tested, the operations of reproduction and crossover may reduce the population diversity of the chromosomes [24,25]. Hence, often mutation probability is introduced to avoid convergence to a non-optimal solution by randomly replacing a gene in a chromosome [24,25].

7.3. Sugarcane factory case study

7.3.1. Sugarcane mill process description

The MATLAB sugar mill model developed by Starzak and Davis [11] for a typical sugarcane mill that processes 250 tonnes of cane/hr under steady-state conditions is used to simulate the operational trends under the combined effect of disturbances and measurements errors. Figure 7-3 is a simplified process flow diagram of a typical sugarcane mill [27]. The steady-state sugarcane model consists of the mass and energy balances of the six main process units, namely the extraction unit with a diffuser system, clarification with mud filtration, five-effect evaporator station, a three-staged crystallization process with a remelt scheme, sugar drying, and utilities (boiler, turbogenerators and cooling tower) [26]. The detailed diagrams for each of the process units are provided in Figures 2.2 to 2.8.

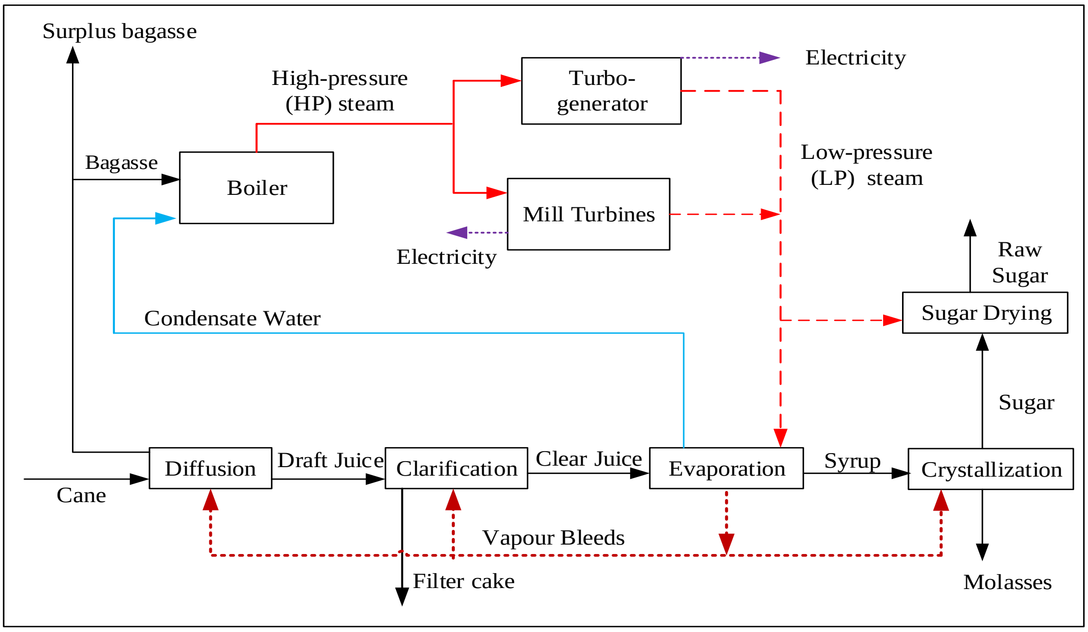

Figure 7-3: Typical Raw Sugar Mill Process in sugar mills

In Figure 7-3 the extraction unit equipment namely the diffuser and the mill turbines which are used for driving the cane knifing, shredding, and bagasse dewatering machinery are separated for more diagrammatic clarity of this section of the sugarcane mill. The first step in raw sugar production is the knifing and shredding of sugarcane to allow for good percolation rates in the diffuser. A diffuser is a carrier tank through which the shredded sugarcane is conveyed, while imbibition water is pumped through in a counter-current manner, to facilitate sucrose extraction. The extracted draft juice (DJ) from the diffuser unit is mixed with filtrate juice and syrup sludge filter before being passed through a train of heat exchangers in the clarification unit [26]. A flash tank is used to remove the dissolved gases from the heated mixed juice (MJ) before being fed in a clarifier [28]. The clarifier removes the impurities from the raw juice that contributes to the opaque color of the sugar juice. The resulting clarified solution is thus called clear juice (CJ). A preheater is used to raise the temperature of the clear juice and to allow for flashing upon entry into the first evaporator effect [28]. An evaporator unit is an energy-intensive unit as it is responsible for concentrating CJ with a dissolved solids (DS) content of 13% to a concentrated syrup of around 68% [27].

The concentrated syrup stream is directed to the A- pan and the mingler in the crystallization unit. After evaporation in the A, B, and C pan the resultant sugar crystals and syrup (massecuite), is cooled, and mixed for further crystallization in the cooling crystallisers. The resulting sugar is passed through the centrifuges to separate the sugar crystals from the syrup. The A-sugar is dried in a rotary dryer, while the C- and B-sugars (not used by the mingler) is dissolved in the re-melter. The resulting remelt stream is fed into the A-pan together with syrup and magma. A and B-molasses streams are recycled to the B and C pans, respectively. The C-molasses is a factory by-product. The fiber residue (bagasse) remaining after the extraction process, is compressed in the dewatering mills to reduce its moisture content before being incinerated in the boiler unit to generate high pressure (HP) steam of 31 bar and 390℃ [26]. The HP steam is used in the mill turbines to provide energy for the extraction unit machinery and to produce electricity in the turbogenerators. The exhausted steam from the extraction unit turbines and the turbogenerators is at a lower-pressure (LP) steam of around 2 bar [26]. The terms high pressure and lower pressure steam are used in this study to differentiate the two streams based on their pressure. The LP steam is used in the first evaporator effect, sugar drier, and deaerator. A portion of vapor generated from the evaporation of water in the first three evaporator effects is used to sustain the energy demands of the extraction, clarification, and crystallization unit.

7.3.2. Steady-state optimal operation

To quantify the plant-wide steady-state operation of a sugarcane mill, the scalar objective function is defined in terms of the products revenue and the raw materials cost in Equation (7-13) [13]:

$$\begin{aligned} J\,(u,d)\ in\,\$/hr \\ &= (\dot{\mathrm{m}}_{\mathrm{SUGAR}} \times \mathrm{P}_{\mathrm{SUGAR}} + \dot{\mathrm{m}}_{\mathrm{MOLASSES}} \times \mathrm{P}_{\mathrm{MOLASSES}} \\ &+ \dot{\mathrm{m}}_{\mathrm{SURPLUS\ BAGASSE}} \times \mathrm{P}_{\mathrm{SURPLUS\ BAGASSE}}) \\ &- (\dot{\mathrm{m}}_{\mathrm{CANE}} \times \mathrm{P}_{\mathrm{CANE}} + \dot{\mathrm{m}}_{\mathrm{LIME}} \times \mathrm{P}_{\mathrm{LIME}}) \end{aligned} \tag{7-13}$$

The symbols $\dot{\mathrm{m}}$ and P denote the flow and prices associated with the products (sugar, molasses, and surplus bagasse) and raw materials (sugarcane and lime) streams, respectively. The price for sugarcane is calculated using the price of the recoverable value (RV) of cane [13]. The value of bagasse depends on the type of supplementary fuel (coal) which would otherwise be used in the factory in case of bagasse shortages. Hence the combined cost of buying and transporting coal to a sugarcane factory is used to determine the price of bagasse while considering their calorific value differences [13]. A coal transportation distance of 90.09 km is assumed [13]. A detailed description of Equation (7-13) is provided in the work by Mkwananzi et al. [13]. Surrogate optimization was used for global optimization of the steady-state sugarcane mill model, assuming nominal values for the external process disturbances and market prices, as provided in SOM, Table S-3. The price of molasses is calculated from the value of sugar by using the sucrose content ratio of the two streams which based on the steady-state sugar mill model is 0.28. The nominal steady-state optimal value as per Equation (7-13) is $\mathrm{J^{opt}(d^*) = US\$3652.81/hr}$. The corresponding steady-state optimal values for the manipulated variables (u) and the candidate measurements (y) are provided in SOM, Table S-4, and SOM, Table S-5, respectively.

7.3.3. Sensor selection objective function formulation

The overall sensor selection objective seeks to find the optimal linear combination of CVs and their corresponding optimal sensor precisions which maximize the net-factory revenue by simultaneously minimizing the revenue loss due to the implementation of self-optimizing control and the total cost of instrumentation. Because of the effect of disturbances and measurement errors in the controllers' attempt to implement self-optimizing control, the average loss, L_{ave} is expressed as the deviation of the attained revenue $J(u, d)$ from the optimal revenue, $J_{opt}(d)$. Based on the exact local method, Equation (7-8) is used to compute the average loss in revenue, Lave. The strategy used in the computation of the first and the second partial derivatives is illustrated in SOM, Figure S-3 using the example for $\mathrm{G^y}$ and $\mathrm{J_{uu}}$. The disturbances considered are sugarcane flow, fiber, sucrose, and DS content, and the air temperature and humidity. The allowable small deviations of the disturbances, $\mathrm{W_d}$=diagonal (3.39,0.28,0.18,0.18,0.51,1.75).

The cost of purchasing equipment is recovered as depreciation cost, over the useful life of the equipment [29]. Several methods can be used to determine depreciation costs [29]. The selection of the method for determining the depreciation costs depends on the accounting practices of a company and the prevailing tax laws of a country [29,30]. Owing to its simplicity, the straight-line depreciation method is often used in the industry by design engineers to report economic evaluations of projects [29,30]. In this method, it is assumed that the equipment cost less its salvage value decreases linearly with time. Thus, the accounting provision is made for equal amounts to be set aside each year throughout the entire lifespan of the equipment [29,30]. Salvage value is the amount that can be attained from the sale of equipment at the end of its lifespan. Based on the straight-line method, the annual depreciation cost is [29]:

$$\text{Depreciation cost (\$/year)} = \frac{\mathrm{V - V_s}}{\text{Lifespan}} \tag{7-14}$$

Where,

V = Equipment cost (US$)

V_s= Salvage value of the equipment after service life in (US$)

For this study, the straight-line method is used to account for the cost of the sensor placements as an annual operating cost such that,

$$\text{Total cost of purchasing the sensors, } J_{sc}\ (\text{US\$/year}) = \sum_{i=1}^{N_c} \frac{\text{Sensor cost}}{\text{Sensor life span}} \tag{7-15}$$

The salvage value of the sensors is assumed to be zero at the end of their lifespan. To incorporate the maintenance costs in a sensor network design problem, the number of maintenance cycles must be known in advance. However, considering the lack of adequate sensors and precise sensors in sugarcane mills, potential sensors that are currently not being used in the study consulted sugarcane mills were obtained from instrumentation companies. As such, the sensor installation and maintenance scheduling and costing information were not available. For these reasons, while also considering that maintenance scheduling policies vary from one factory to another, only the sensor purchasing cost normalized based on the sensor lifespan was considered in this study.

To make sure that the financial units used are the same the sensor life span is converted to hours such that J_{sc} is in US\$/hr. Therefore, the overall sensor selection objective for the sugarcane mill is defined as:

$$\text{Net revenue, } J_T\ (\text{US\$/year}) = J_{opt}(d^*) - (L_{ave} + J_{sc}) \tag{7-16}$$

The economic objective is to select a sensor combination that maximizes the net factory revenue, as per Equation (7-16). Hence in the genetic algorithms, this is formulated as the minimization of the negative net income, $-J_T$.

7.3.4. Genetic algorithms description

For self-optimizing control, the manipulated variables of interest are those whose adjustment has an impact on the defined scalar cost function, $J(u, d)$. In this regard, the degrees of freedom available for optimization of the factory economics are required and not necessarily the degrees of freedom available for control [7]. For this study, the sugar mill process is considered to have 41 remaining degrees of freedom u to use for optimization. There are 78 available candidate measurements (y) for use in the selection of the optimal sensor network and six disturbance variables. The 78 candidate CVs comprise temperature, pressure, moisture, and dissolved solids (DS) content measurements. For each of the 78 candidate measurements, 3 alternative sensors were obtained from surveys distributed to sugarcane factories and sensor distribution companies (SOM, Table S-6). The number of variables that can be independently controlled is equal to the number of independently manipulated variables. Thus 41 linear combinations of measurements are selected from the 234 available sensors and this results in several alternative combinations to be evaluated for optimal sensor placement. Hence GAs is used in this study to enable a more efficient search for optimal sensor placement. The restrictions that the maximum sensor location for each variable is 1 and that the sum of each chromosome is always 41 were also added in the GAs routine. All GAs calculations were coded in MATLAB 2019b. The parameters used for GAs are given in SOM, Table S-7.

7.4. Results analysis and discussion

7.4.1. Optimal sensor placement using genetic algorithms

Using GAs, the optimal linear combination of 41 CVs and their corresponding optimal sensor placements that can be used for self-optimizing control in the sugarcane mills were obtained. The optimal linear CV combinations are provided in Table 7-1, together with the corresponding errors of the selected sensors as achieved by the optimization routine. The net-revenue, total instrumentation purchasing cost, and average loss in US$/hr for the optimal sensor placement are 3586.47, 4.41, and 61.93, respectively (Table 7-2). To evaluate the benefits of the optimal sensor placement found in the present study, a base case sensor placement of a typical sugarcane mill was defined by using the same 41 optimal linear CVs but assigning for their measurements the sensors commonly used in the sugar industry (SOM, Table S-6). These measurement errors for temperature, pressure, and concentration for the base case sensor placement are also given in Table 7-1. The net-revenue, total instrumentation cost and average loss in US$/hr for the base case sensor placement design are 3490.80, 4.30, and 157.72 (Table 7-2). Appendix D illustrates the allocated optimal sensor placements (Table 7-2) in different process units in a sugarcane mill.

Table 7-1: Optimal linear CV combinations with optimal and non-optimal (base-case) sensor placements. Stream abbreviations are in Table 2-1 to 2-6.

Temperature			Pressure			Concentration		
Optimal linear CV streams	**Optimal measurements error**	**Base case measurements error**	**Optimal linear CV streams**	**Optimal measurements error**	**Base case measurements error**	**Optimal linear CV streams**	**Optimal measurements error**	**Base case measurements error**
SD2	0.15 +0.2%	0.15 +0.2%	SD2	0.30%	0.17%	BAG DS	1%	1%
SD6	0.15 +0.2%	0.15 +0.2%	SB1	0.04%	0.17%	FC sucrose	1%	1%
SDH	0.15 +0.2%	0.15 +0.2%	SD6	0.04%	0.17%	L2 DS	1%	1%
MJF	0.15 +0.2%	0.15 +0.2%	SD4	0.17%	0.17%	L3 DS	1%	1%
SYR	0.15 +0.2%	0.15 +0.2%	PANC	0.17%	0.17%	L4 DS	1%	1%
S2	0.15 +0.2%	0.15 +0.2%	SBO	0.17%	0.17%	PANC DS	0.05%	1%
SEH	0.15 +0.2%	0.15 +0.2%				MASC DS	0.05%	1.50%
MASA	0.3+0.5%	0.15 +0.2%				SYR DS	0.15%	1.00%
SUAH	0.3+0.5%	0.15 +0.2%				MJ DS	0.15%	1.00%
CTW	0.3+0.5%	0.15 +0.2%				MASA DS	0.15%	1.50%
SHP	0.3+0.5%	0.15 +0.2%				BAG Moisture	0.10%	0.10%
S4	0.3+0.5%	0.15 +0.2%						
SD4	0.1+0.0017	0.15 +0.2%						
MJ2	0.1+0.0017	0.15 +0.2%						
PANC	0.1+0.0017	0.15 +0.2%						
WK	0.1+0.0017	0.15 +0.2%						
SUAD	0.1+0.0017	0.15 +0.2%						
EXSS	0.1+0.0017	0.15 +0.2%						
DJ	0.1+0.0017	0.15 +0.2%						
L1	0.1+0.0017	0.15 +0.2%						
S1	0.1+0.0017	0.15 +0.2%						
SKA	0.1+0.0017	0.15 +0.2%						
SKC	0.1+0.0017	0.15 +0.2%						
SB2	0.30%	0.40%						

Table 7-2: Economic evaluations for the optimal and base case sensor placement

Evaluations	**Net-revenue (US$/hr)**	**Average loss (US$/hr)**	**Total sensor network cost (US$/hr)**
Optimal sensor placement	3586.47	61.93	4.41
Base case sensor placement	3490.80	157.72	4.30
Cost of the precision upgrade of base case sensor placement	US$2.23/hr		
Unnecessary sensor expenditure incurred in the base case network for self-optimizing control	US$0.04/hr		

While the base case sensor placement, which uses the typical sensors found in sugarcane mills, has a lower instrumentation cost, this is shown to be associated with an increased average revenue loss thus ultimately reducing the attainable profits. Having precise sensors allows the operation of a factory closer to constraints, which garner more revenue as illustrated by the low average loss and high net revenue of the optimal sensor placement network [31]. Previous studies have shown better self-optimizing properties when linear CV measurements are used instead of single measurements [9,19]. Therefore, by extending the self-optimizing control concept beyond the selection of CVs, the present study has further shown that the self-optimizing properties of a factory can be improved when the selection of CVs is coupled with optimal sensor placements.

By comparing the optimal and base case sensor errors in Table 7-1, it is observed that 19 out of the 41 optimal measurements require more precision as compared to the currently used measurements in the sugarcane mills. These 19 CVs comprise 12, 2, and 5 temperature, pressure, and concentration measurements, respectively. Therefore, the observed low average loss for the optimal sensor placement is attributed to the use of more precise sensors for these 19 CVs as compared to the sensors currently employed in the sugarcane industry. For a factory whose sensor placement is characterized by that of the base case sensor placement, the cost of upgrading the precision of these 19 CVs is US$2.23/hr (Table 7-2), which is only 12% more than the cost of the typical sensors used in sugarcane mills for these CVs. Also, considering the difference in the average revenue loss for the optimal and base case sensor placements, there is sufficient motivation to purchase the allocated precise sensors for these 19 CVs.

The strategy used in this present study to compare the optimal and base case sensor placements allows for the identification of CVs whose precise measurements are more essential and those whose precision is not crucial for self-optimizing control. From the present study results, there are 6 CVs (5 temperature and 1 pressure) in the optimal network that require less precision compared to the currently employed measurements in typical sugarcane mills. Therefore, although these CVs are essential for self-optimizing control, the propagation of their measurement errors has a smaller effect on the factory economics such that purchasing more precise sensors for these CVs is unnecessary for the industry. The cost of purchasing these 6 sensors in the base case placement is US$0.07/hr, while in the optimal sensor placement their sensor costs sum up to only US$0.03 /hr. Therefore, by using a systematic method for optimal sensor placement, unnecessary sensor expenditures (Table 7-2) can be identified thereby resulting in the industry saving money for other energy improvement projects.

7.4.2. Evaporator and crystallization unit

For the sugarcane industry, the improvement of energy efficiency can position the industry to play a key role in the large-scale commercialization of bio-based products from surplus bagasse, while simultaneously improving its economic viability [32]. The application of the multiple-effect evaporator systems in the sugar mills makes it possible to meet all the process energy requirements from the available bagasse, while simultaneously generating surplus bagasse for use in the production of bio-based products [27]. The longest sustained perturbation in the evaporator unit is due to its coupling with the batch vacuum pans in the crystallization unit through vapor demands and feed supply (syrup) [33]. The evaporator and crystallization unit is responsible for approximately 35 % of bagasse energy usage, therefore, their adequate control in the presence of disturbances is important for improving the plant-wide economics.

From the study results in Table 7-1, the optimizer assigned DS content sensors that measure syrup, A, and C massecuite (displayed as SYR, MASA, and MASC in Table 7-1, respectively) more precisely compared to the typical sensors used in the sugar industry. The fact that the optimizer captured these CVs as part of the optimal linear measured CVs for self-optimizing control and allocated more precise measurements for these CVs agrees with actual operational experiences on their importance. The single vessel vacuum pans have a lower evaporation efficiency compared to the multiple effect evaporation. Therefore, if low syrup DS content is attained, it forces the evaporation of the additional water in the syrup to be carried out in the less energy efficient A-pan, thereby leading to excessive energy demands in the crystallization unit. Commercial sugar is produced from the A-stage of the crystallization unit, therefore adequate control of the A-vacuum pan by achieving high A massecuite DS content is crucial for maximizing sugar production and minimizing excess energy usage due to elevated massecuite recycling. On the other hand, the control of the C massecuite DS content must be done in such a way that sucrose losses in the C-molasses stream exiting the factory are minimized without excessive usage of energy.

Digital refractometers were introduced in the early 80s for the measurement of DS concentration and were employed in the sugar industry [34]. However, new and improved digital refractometers for measuring the DS concentration with measurement errors as low as 0.05% and 0.15% have been coming up in the market [34–36]. These refractometers are reported to be able to take DS concentration measurements without being affected by entrapped air bubbles, undissolved components, and color variations in the products [36]. Massecuite is a mixture of sugar crystals and syrup hence it is important to be able to measure the DS concentration of the liquid phase throughout the crystallization batch process without interference from the growing sugar crystals in the pans. This aspect is especially crucial for the reliable automatic control of the vacuum pans and the evaporator unit. The cost of a sensor tends to increase with its precision, therefore the fact that more precise sensors for syrup, A, and C massecuite were selected by the optimizer while improving the plant-wide economy further emphasizes the importance of these variables. To ensure the prescribed sensor precisions are maintained in factory installations factors such as the field location of the sensor, sensor maintenance and calibration must be considered.

To evaluate the energy impacts of using the optimal sensor placements of syrup, A, and B massecuite DS content compared to the base case sensors, 100 uniformly distributed values of these CVs were simultaneously taken. Before being simulated in the sugarcane mill model, the generated samples were adjusted based on their corresponding errors in the optimal and base case network. The use of the precise measurements of syrup, A and B massecuite DS content (0.15, 0.15, and 0.05 %) compared to the base case measurement precisions (1, 1.5, and 1.5%) is shown in Figure 7-4 to result in reduced overall factory vapor demand and increased surplus bagasse availability. Such improvements to process control because of more precise DS measurements can allow for a relatively large bagasse-processing bio-refinery annexed to a sugarcane factory. The potential economic benefits from such bagasse valorization, for example through the increased scale of processing in an annexed biorefinery, were not considered in the present optimization methodology.

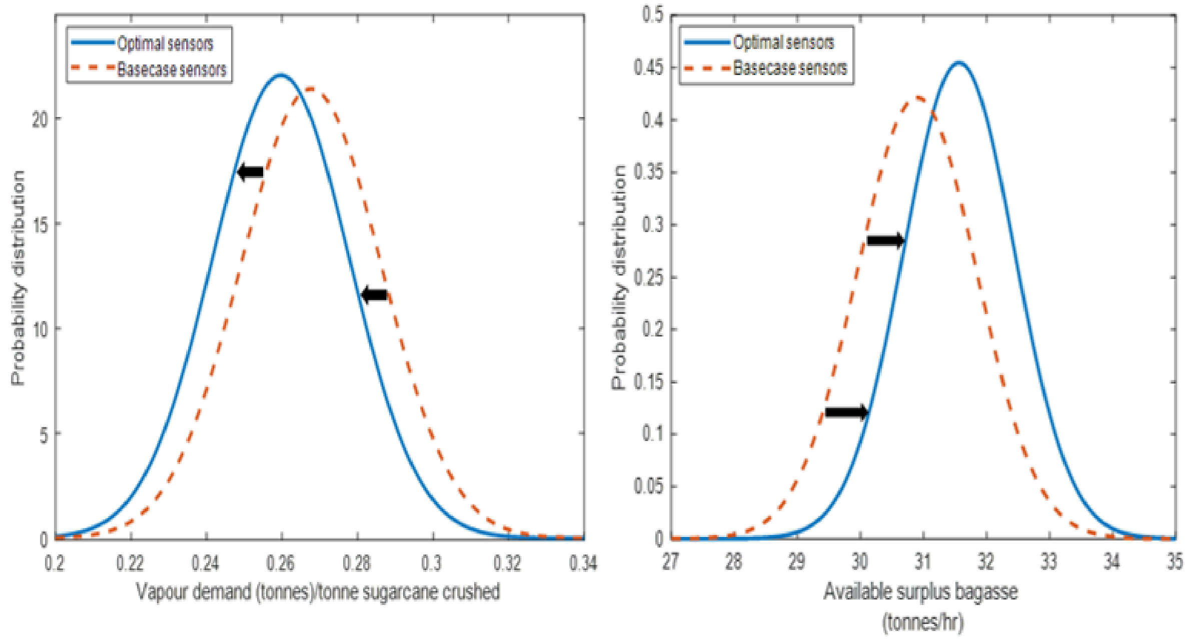

Figure 7-4: Difference in vapor demand and available surplus bagasse when the syrup, A and C massecuite DS measurements from the optimal and base case network are used

7.4.2.1. Supersaturation on-line monitoring

Supersaturation is the driving force of the crystallization process [35]. Supersaturation is the ratio of the sucrose content in solution to sucrose content needed to saturate the solution at the same temperature. Hence, the rate of crystal growth and nucleation is dependent on the existing supersaturation in the solution. If the speed of evaporation is higher than required, excessive supersaturation will occur resulting in unwanted nucleation, poor circulation, the formation of crystal doubles, and conglomerates [35]. If the attained supersaturation point is less than desired, it leads to loss of already crystallized sugar by dissolving in the mother liquor [35]. This loss of crystallized sugar results in excess energy demands in the vacuum pans from the re-evaporation of already evaporated liquor. The crystallization unit relies on the evaporator unit for vapor supply; hence such excess energy demands impact the control of the evaporator unit. There is no single instrument able to measure supersaturation, because it is a function of several variables like the DS concentration and purity of liquid phase in A- massecuite, A-massecuite temperature, and the syrup concentration variables [35].

However, with the introduction of the SeedMaster device, on-line calculation of supersaturation, real-time monitoring of sugar crystals growth, control of automatic or manual seeding, and transmission of massecuite variables has become a reality [37,38]. Of interest is that the optimal sensor placement for the A-massecuite is amongst the digital refractometers that have been successfully used together with a SeedMaster device for online monitoring of sugar crystallization in sugar refineries and the beet sugar industry. Therefore, more benefits can be attained if the more precise digital refractometers found in the present study for A-massecuite and syrup are coupled to a crystallization transmitter and seeding device like the SeedMaster. Rosza [35] comments on outdated pan control strategies and several inaccurate beliefs surrounding the operation of the vacuum pan in the sugar industry. On the other hand, Rozsa et al. [37] argue that the available dynamic models for sugar crystallization based on material, energy, and crystal population balance equations often provide questionable results when their use is attempted in actual vacuum pan operation. The SeedMaster organizes and archives all the data trends relating to each batch process [37,38]. This ability is crucial for an improved understanding of the operational dynamics in the batch pans, thereby resulting in the accurate simulation of the crystallization batch processes and the implementation of advanced control systems that can alleviate their impacts on the evaporator unit.

7.4.3. Boiler unit

The boiler is responsible for approximately 29% of the bagasse energy wastage through heat losses. The net calorific value (NCV) of bagasse is defined as:

$$\mathrm{NCV} = [18260 - 207.01\mathrm{Moisture} - 182.06\mathrm{Ash} - 31.14\mathrm{DS}] \tag{7-17}$$

Therefore, to increase the value of bagasse as a fuel in the boiler unit, the moisture, ash, and DS content of bagasse must be maintained as low as possible. Furthermore, an increase in the DS content of bagasse denotes increased sucrose losses through the bagasse stream. Although the optimizer found no justification for improved sensor precision of bagasse moisture and the DS content, their significance on the sugarcane mill operations was captured such that they were still selected as CVs for self-optimizing control. The ash content was not added as part of the candidate measurements, as it is not modeled in the MATLAB sugarcane mill model used in the present study. However, in general, if the bagasse DS content is high, the likelihood of increased alkali metals in the bagasse ash is high. Alkali metals impede the heat transmittance in the boiler, and in doing so reduce the boiler efficiency. The dewatering mill and the attained sucrose extraction efficiency in the diffuser determine the attainable bagasse moisture and DS content. Therefore, adequate control of these machineries is urged for reducing the bagasse energy wastage in the boiler unit.

7.4.4. Monte Carlo sensitivity of the sensor placements

The selection of the optimal sensor placement using the self-optimizing control concept is applied to an instance of small variations around the nominal values of the disturbances. This obscures the actual factory variations of these disturbance variables, which can at times vary more widely from the nominal disturbance value. Hence the problem that might arise from such a set-up is that the optimal sensor network is only valid for the deviation magnitudes considered and not robust enough to handle instances of increased disturbance deviations. Moreover, despite the general acknowledgment of the volatile market prices of the raw materials and product streams in the sugarcane factory, the mean values of the market prices were maintained throughout the sensor selection study [32]. Therefore, to overcome these shortcomings and test the robustness of the optimal and base case sensor networks under the random variations of both the process disturbances and market prices, a stochastic (Monte Carlo) method was used. The Monte Carlo approach was used to generate 3149 random input values of each disturbance and market price from their probability distributions. The data used to generate the probability distributions was obtained from [13]. For each network design, the random samples of the disturbances and market prices are simulated using the sugarcane mill and financial models, respectively, and the output distributions of the average revenue loss are generated. The resulting distributions for the average loss for the base case and optimal sensor placements are provided in Figure 7-5.

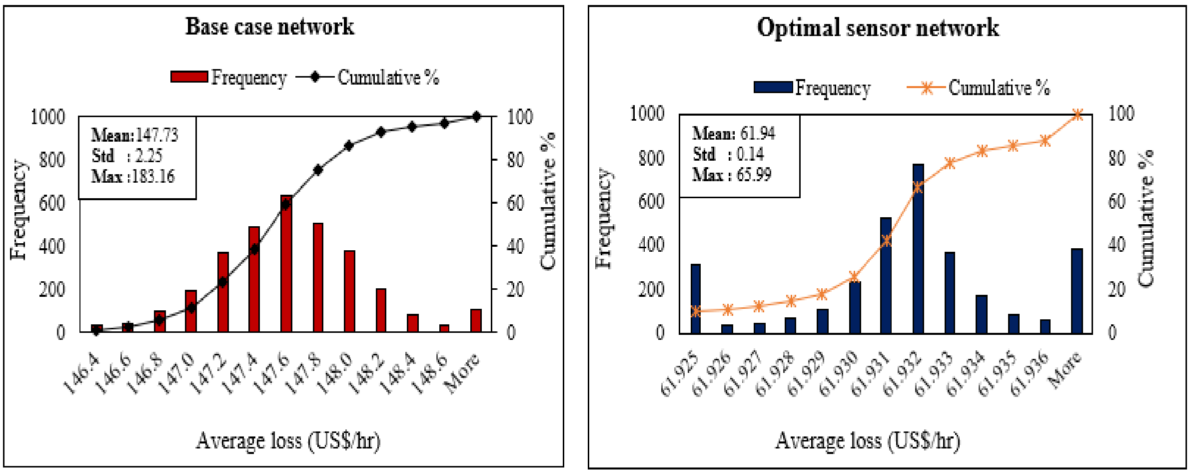

Figure 7-5: Variation in average loss with the random variations in the disturbances and market prices

From the differences in the standard deviations, it is observed that the optimal sensor placements are more robust and resilient to deviations in both the external process disturbances and market prices as compared to the base case sensor placements. For the optimal sensor placement, the maximum revenue loss is 64% lower than the maximum loss retained when the base case network is used. This reduction in revenue loss coupled with only a 2% increase in total instrumentation cost for the optimal sensor placements suggests that it is favorable to purchase the optimal measurements. Hence, it can be concluded that the optimal sensor placement is more robust and resilient to the random variations in the disturbances and market prices compared to the base case sensor placements.

Without precise measurements of energy consumption, the areas of energy wastage and potential energy saving are uncertain. Moreover, having precise sensors allows the operation of a factory closer to constraints which garner more revenue and energy savings. The optimal sensor placement allocated improved sensor precisions for 19 CVs relative to the typical industry sensor placement for these variables. Based on the same Monte Carlo runs, the resulting output distributions of the energy indicators were evaluated, and the resulting summary statistics are provided in Table 7-3. Table 7-3 provides the maximum, mean, and standard deviations of the energy indicators when either the optimal sensor placement or the typical industry sensor placement is used.

Table 7-3: Summary statistics for the energy indicators for the optimal and typical industry sensor placements in the presence of external process disturbances and market price variations

Energy indicators	Maximum	Mean	Standard deviation	Maximum	Mean	Standard deviation
	Optimal sensor placement			Typical industry placement		
Evaporator energy indicator	0.24	0.22	0.003	0.25	0.23	0.003
Total massecuite recycling	1.40	1.13	0.016	1.50	1.21	0.017
Boiler efficiency (%)	68.73	66.75	0.44	68.43	66.32	0.52
Vapor demand per tonne cane	0.30	0.25	0.018	0.32	0.28	0.033
HP demand per tonne cane	0.41	0.39	0.007	0.42	0.39	0.009
HP demand per tonne sugar	3.49	3.27	0.068	3.55	3.34	0.076
Surplus bagasse (tonne/hr)	33.17	31.56	0.876	32.64	30.89	0.947
Steam generating cost (US$/tonne HP steam)	29.61	16.78	4.01	30.11	17.28	4.51

Overall, the use of the more precise measurements in the optimal sensor placement is shown to result in improved energy usage in the factory compared to the typical industry sensor placement. Based on the mean differences in Table 7-3, there is a 7.10% and 10.71% reduction in total massecuite recycling and the total vapor bleed demand per unit sugarcane when the optimal sensor placement is used instead of the typical industry sensor placement. This reduction is mainly attributed to the improvements in the DS content measurements of mixed juice, syrup, and the A and C massecuite streams. The increase in surplus bagasse coupled with the 2.14% reduction in the HP steam demand per unit sugar also shows that the use of precise measurements can allow a factory to gain from bagasse revenue or to be annexed to a relatively larger biorefinery that uses bagasse as feedstock. The reduced standard deviations in Table 7-3 indicate that the use of precise measurements allows for improved robustness and resilience towards external process disturbances as compared to the typical industry sensor placement. The cost of generating HP steam is shown to decrease by US$0.50/hr when the optimal sensor placement is used instead of the typical industry placement. This reduction combined with the reduced HP steam demand also shows that the production costs of a factory can be minimized by using precise sensors.

7.4.5. Performance evaluation: Self-optimizing and set-point optimizing control

Self-optimizing control is based on a constant set-point policy [13], while set-point optimization seeks to maximize profitability by finding the optimal CV set-points when disturbances occur [28]. Relative to set-point optimization, self-optimizing control is the non-optimal operation. For these reasons, also assuming the implementation of each sensor network design (optimal and base case sensor placements), set-point optimization was conducted for the 3149 scenarios of the random variations in the process disturbances and market prices. Fourteen CVs established from the work by [28] were used as decision variables in the set-point optimizer. These CVs are the stream temperatures of [PWH; MJ1; MJ2; MJ3; L0; PANA; PANB; PANC; REMC] and the stream concentrations of [SYR; PANA; PANB; PANC; REMC]. This strategy is illustrated in Figure 7-6.

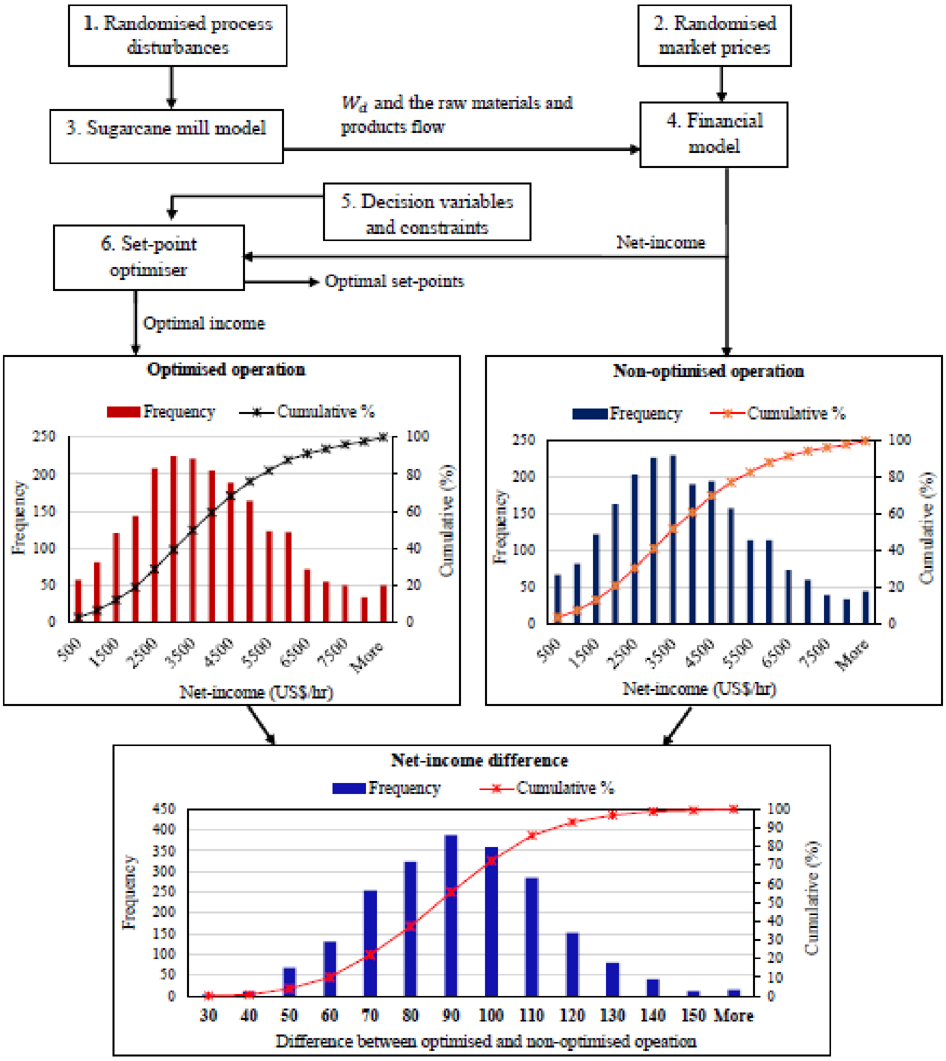

Figure 7-6: Comparison of each sensor network performance when self-optimizing control or set-point optimization is implemented (Difference in net-income is in US$/hr).

The quantified net-income difference for set-point optimized operation and self-optimizing control (constant set-point policy) for each network when random variations in the process disturbances and market prices occur are provided in Figure 7-7. Based on Figure 7-7, there is more revenue loss for the base case network when a constant set-point policy is implemented compared to the case when set-point re-optimization is done with the occurrence of process and market price disturbances. Although the optimal network incurs revenue loss when re-optimization is not done, the incurred loss is almost half of that attained when the base case network is used. Hence the methodology used in the present study to find an optimal sensor network helps to reduce revenue loss while simplifying operation by not having to re-optimize when disturbances occur.

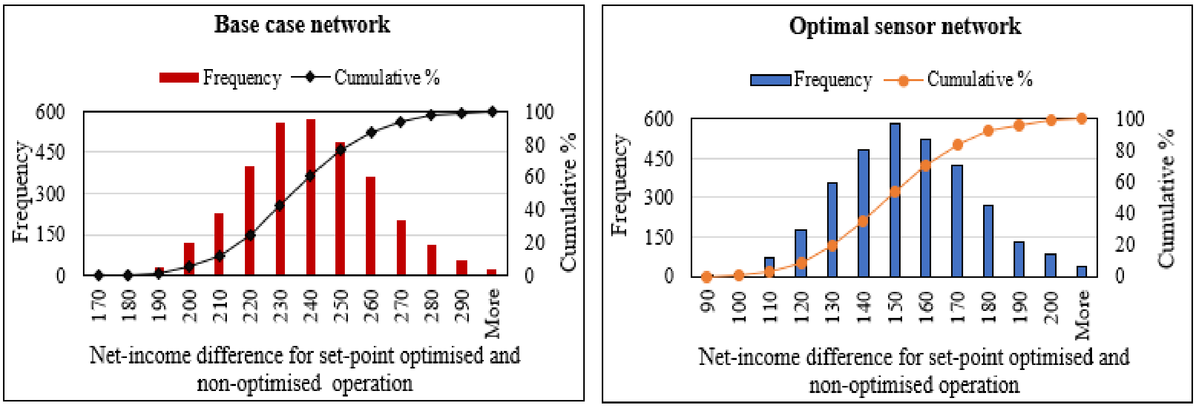

Figure 7-7: Net-income differences for set-point optimized and self-optimizing control for the base case and optimal sensor network

7.4.6. Required set-point optimisation frequency

Self-optimizing control seeks to reduce or even eliminate the number of times the optimizer is updated when disturbances occur while achieving minimal revenue loss. To determine the frequency required for set-optimization when each network is used, different acceptable revenue losses are enforced and statistical analysis is done based on the quantified net-income differences in Figure 7-7. Thus, for instances when the difference between the non-optimal and optimal net-revenue surpasses the factory assigned or approved revenue loss, set-point optimization is required. Table 7-4 provides information on the required frequencies for set-point optimization for each network under the random variations of the process disturbances and market prices. Both the base case and the optimal sensor network are observed to perform poorly when an acceptable loss of less than US$100/hr is enforced. However, when the acceptable loss is increased to values greater than US$100/hr, a significant decrease in the required frequency of set-point optimization is observed for the optimal network compared to the base case network. Hence for actual implementation, factories can assign their acceptable revenue losses and use this to only schedule set-point optimization for instances when the loss incurred surpasses the factory-approved loss.

Table 7-4: Required frequency of set-point optimisation with process and market price disturbances

Acceptable loss without re-optimizing (US$/hr)	**Set-point optimisation frequency (%)**	
	Base case network	Optimal network
Less than 50	100.00	99.97
Less than 100	100.00	99.36
Less than 150	99.97	46.52
Less than 200	95.05	1.27
Less than 250	23.75	0.00

7.5. Conclusions

Considering the high frequency of disturbances in a sugarcane factory, the unavailability of online measurements for disturbances, and the inconvenience of frequently re-optimizing operations, the implementation of self-optimizing control is considered. Self-optimizing control deals with using the model offline to find an appropriate set of CVs that can be kept at constant set-points without re-optimizing when disturbances occur. The objective is to translate economic objectives into control objectives. This may eliminate the need for an expensive online optimizer to re-optimize when disturbances occur or at least the re-optimization may be performed less frequently. While avoiding online re-optimization, this constant-set-point policy does lead to a revenue loss, L as compared to the truly optimal case where re-optimization is done with the ingress of disturbances. The self-optimizing control principle has been used in previous studies to select the linear CVs based on fixed sensors, however, in the present study, the concept was used for the simultaneous selection of 41 optimal linear CVs and their optimal sensor placements. Sensor selection is performed within a set of available sensors of known precision and cost. Optimality is defined as maximizing the net-revenue by minimizing the total instrumentation cost and the revenue loss due to the combined effect of the disturbances and measurement errors on the controllers' attempt to implement self-optimizing control. Genetic algorithms were used for optimization.

The economically optimal sensor placements found in this study had an average revenue loss of US$61.93/hr as compared to the base case sensor placement which had a loss of US$157.72/hr. These losses correspond to total instrumentation costs of 4.41 and 4.30 US$/hr, respectively. By comparing the optimal and base case sensor errors it was observed that 19 out of the 41 optimal CVs measurements were shown to require more precision as compared to the currently used measurements in the sugarcane mills. The cost of upgrading the precision of these 19 CVs is US$2.23 /hr which is only US$0.23/hr more than the cost of the typical sensors used in sugarcane mills for these CVs. Hence considering the difference in the average revenue loss for the optimal and base case sensor placements, there is sufficient motivation to purchase the allocated precise sensors for these 19 CVs. Six CVs in the optimal sensor network was shown to require less precision compared to the currently employed measurements in a typical sugarcane mill. Although these CVs were found to be essential for self-optimizing control, the propagation of their measurement errors has less effect on the factory economics such that purchasing more precise sensors for these CVs is unnecessary for the industry. By using a systematic method for optimal sensor placement, the present study was able to identify unnecessary sensor expenditures and areas requiring precision upgrade for self-optimizing control of sugarcane mills.

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Chapter 8

8.Conclusions and Recommendations

8.1. Conclusions

Energy efficiency improvement in sugarcane mills can help to increase the economic viability of the industry through additional revenue from the valorization of bagasse and molasses. Therefore, the overall aim of this study is to develop an improved energy management system for sugarcane mills through enhanced process monitoring and plant-wide control. A typical sugarcane factory that processes 250 tonnes of sugarcane per hour at steady-state conditions was considered. The approach used included identifying the variables with the largest influence on energy efficiency, evaluating their sensitivity to disturbances, and investigating possible control policies for improving energy and economic efficiency in the presence of disturbances. The primary objectives set out in Chapter 3 to address the sugar industry needs for improved energy and economic efficiency are:

1. Determine the CVs whose steady-state deviation leads to excess energy consumption through energy indicator definition, sensitivity, and statistical analysis
2. Evaluate the stochastic risks associated with random variations in the external process disturbances and market prices
3. Investigate the potential benefits of implementing set-point optimizing control when process disturbances and market price variation occur.
4. Determine the optimal linear CVs combination and their optimal sensor placements for plant-wide self-optimizing control of sugarcane mills when disturbances occur.

Objective 1 is addressed in Chapters 4 and 5 for the production units and the boiler unit, respectively. **In Chapter 4**, energy indicators for the evaporator, crystallization, and overall factory operations were defined to allow for quantification of the energy performance of the major energy-using units and the overall factory energy perspective. The syrup DS content and the extent of massecuite recycling were observed to be the CVs whose steady-state deviation resulted in energy inefficiencies in the evaporator unit operations. The reliance of the batch vacuum pans on the evaporator unit for vapor supply is considered as one of the contributing factors to the inefficient operation and control of the evaporator unit. Hence the syrup and A, B, and C massecuite DS contents were identified as the CVs to be controlled to manage the interaction between the evaporator and crystallization unit and to ultimately maintain improved energy efficiency.

In **Chapter 5**, energy (and economic) indicators were defined for the boiler unit comprising of a deaerator system. The moisture content of bagasse was observed to have the largest influence on the boiler efficiency while the temperature of the condensates returned as boiler feedwater was observed to have the largest impact on the deaerator energy efficiency. Hence the boiler efficiency was observed to rely on the efficient operation of the dewatering mills (extraction unit) and the evaporation unit, which are responsible for bagasse and return condensates supply. The bagasse moisture content had the largest influence on the HP steam-generating cost, followed by flue gas temperature, excess air, return condensate temperature, and lastly, the percentage of cold water used as feedwater. Some of the study defined energy indicators from the fulfillment of objective 1 have since been acknowledged by the South African sugarcane mills.

When designing a control structure for optimal operation and control, it is important to understand how the process variables change with disturbances. Therefore, in **Chapter 6**, objectives 2 and 3 were addressed by firstly investigating the stochastic risks associated with variations in external process disturbances and market prices and evaluating the benefits of implementing set-point optimizing control. Fourteen CVs including those identified from Chapters 4 and 5 to influence the sugarcane mill energy efficiency were selected for use as decision variables for the set-point optimizer that seeks to maximize the factory net-revenue in the presence of disturbances. The strategy used in the present study for defining the plant-wide economics, selecting the CVs for use in the optimizer, and choosing the optimization algorithm was shown to result in improved energy and economic efficiencies in the sugarcane mill operations. The evaporator unit is responsible for sustaining the vapor demands of the extraction, clarification, and crystallization unit. The application of the multiple-effect evaporator systems in the sugar mills makes it possible to meet all the process energy requirements, while simultaneously generating surplus bagasse. With set-point optimization, the total vapor demands from these units were reduced by 14%. Massecuite recycling was observed from objective 1 to result in excess energy demands and with set-point optimization, massecuite recycling was reduced by 23%. Surplus bagasse increased by 8.5% with a satisfactory 0.43% reduction in sugar yield and a 2.4% increase in net revenue.

Therefore, the proposed strategy for set-point optimizing control managed to find the global maxima at which the loss in surplus bagasse revenue due to excess energy use (to minimize sugar loss) no longer justifies the revenue gain from sugar. This is a crucial aspect for the sugar manufacturers as one of the challenges incurred during operation is the balance between sugar production and energy usage improvement. Furthermore considering, the global shift towards bio-based products, the increase in available surplus bagasse coupled with a 6.3% increase in HP steam makes it possible for a relatively large bio-refinery that uses bagasse as feedstock to be annexed to a set-point optimized sugarcane factory. Nine CVs out of the 14 considered in this study were observed to have optimal set-points that are robust and resilient to variations in the process disturbances and market prices. These variables are the temperature of press water after heating, temperatures of mixed juice after each clarification unit heater, B and C massecuite temperatures, A and C massecuite DS content, and re-melt DS content. Hence, for the implementation of optimal steady-state control, the present study suggests a simplified optimal control policy in which these 9 CVs are held constant at their optimal set-points while set-point optimization is done for the remaining 5 CVs. The clear juice temperature after the pre-heater, syrup DS content, A-massecuite temperature (or A- operating pressure), B-massecuite DS content and remelt temperature were found to be the CVs that require set-point re-optimization when disturbances occur.

Overall, the study was successful in formulating a plant-wide set-point optimization structure that can assist in mitigating the stochastic risks related to disturbances, while providing an unbiased method for balancing between energy usage and sugar yield improvement. This is the first study to consider the implementation of plant-wide set-point optimization of the sugarcane mills. Although the strategy of set-point optimization is useful in ensuring optimal factory operation and profitability when disturbances occur, it can be practically intractable for sugarcane mills with frequent disturbances or no online measurements for the disturbances. In self-optimizing control, instead of trying to achieve the best possible economic performance, a small trade-off is made between optimal factory operation and the simplicity of not requiring re-optimization when disturbances occur. In this regard, the implementation of self-optimizing control through the selection of linear CVs combination and their optimal sensor placements (Objective 4) was investigated in **Chapter 7**. The selection of 41 optimal measurements for use as self-optimizing CVs was considered to enable independent control based on 41 remaining degrees of freedom (manipulated variables). Optimality was defined for maximizing the factory revenue by minimizing the cost of instrumentation and the average loss in revenue due to implementing self-optimizing control. The average revenue loss is the difference between the revenue when continuous real-time optimization is done with the occurrence of disturbances and the revenue when no real-time optimization is done.

An economically optimal sensor placement was found with an average revenue loss of US$61.93/hr as compared to the typical base case sensor placement in sugarcane mills which has a loss of US$157.72/hr. These losses correspond to an instrumentation cost of 4.41 and 4.30 US$/hr, respectively. The substantial reduction in average revenue loss for the optimal sensor placement is accredited to 19 CVs which were observed to require more precise measurements for their effective use in facilitating self-optimizing control. Therefore, for a factory hoping to implement self-optimizing control the cost of procuring the precise sensors for these 19 CVs is US$2.23/hr which is only 2% higher than the cost of the imprecise sensors used for these CVs in a typical sugarcane mill. Hence considering the magnitude of improvement in the average revenue loss with the optimal sensor placement there is sufficient motivation for the industry to purchase these more precise sensors for these 19 CVs. There are 6 CVs (5 temperature and 1 pressure) in the optimal sensor network that require less precision compared to the currently employed measurements in sugar mills. Therefore, although these CVs are essential for self-optimizing control, the propagation of their measurement errors has less effect on the factory economics, and purchasing more precise sensors for these CVs is unnecessary for the industry. Hence the study was able to identify the optimal linear CVs measurements for self-optimizing control in sugarcane mills, while also identifying unnecessary instrumentation expenditures and the CV measurements requiring a precision upgrade.

Moreover, the strategy employed in this study for optimal sensor placement managed to identify the importance of the sucrose loss streams by identifying filter cake, bagasse, and C-molasses DS content as part of the self-optimizing control variables. This study was the first to consider self-optimizing control for the simultaneous formulation of the optimal selection of linear CVs and their measurements (sensor) error specifications as previous studies have considered the concept of the selection of linear CVs based on fixed measurements. Furthermore, this is the first study to consider the systematic selection of CVs and measurements for the plant-wide control of sugarcane mills. Overall, this dissertation study was able to address the sugarcane industry's needs to manage energy and economic inefficiencies while contributing to the existing knowledge in literature.

8.2. Recommendations

Based on the results and findings of this present dissertation, the following recommendations are suggested:

1. In chapter 5 an increase in the syrup DS content was observed to lead to increased vapor flow to the barometric condenser. Furthermore, the total vapor demands of the sugarcane mills operations were reduced by 14% with set-point optimization while the optimal sensor placement allows for precise energy estimation and control. Therefore, it might be insightful to evaluate if further energy improvements can be made through pinch analysis and optimal vapor bleed reconfiguration.
2. Future work is recommended for improving the system accuracy beyond sensor accuracy through data reconciliation and for considering the optimal sensor placements of less than 41 CVs by holding some manipulated variables constant. A structured selection of the manipulated variables to hold constant is required. This can be done based on the effect of the manipulated variables adjustments on the plant-wide economics or its capabilities in disturbance effect rejection.
3. Batch to batch (run to run) or within batch optimization strategies is often adopted in real-time optimization of batch processes in the presence of disturbances. For within batch optimization, optimizing control is done during the batch processes for current dynamics. However, such a control structure is often challenging to implement in practice. Hence run-to-run optimization which uses the repetitive nature of the batch process and the information from the previous batch to optimize the next batch is often preferred in practice. Therefore, future work is recommended for using the recently introduced extension of self-optimizing control for batch-to-batch optimization for optimizing the crystallization unit batch operations. This entails the use of a dynamic model of the crystallization process to find the self-optimizing CVs that are resilient to the batch process-related dynamics and can thus be used as constant CVs for run-to-run optimization of the crystallization batch process.
4. Through set-point optimization and optimal sensor, placement increased surplus bagasse availability was observed. Such improvements can potentially allow for a relatively large bagasse-processing bio-refinery to be annexed to a sugarcane factory. However, the potential economic benefits from such bagasse valorization, for example through the increased scale of processing in an annexed biorefinery, were not considered in the present study and hence future work in this area is recommended.

Appendices

Appendix A1: Questionnaire template

Section A: Operational Characteristics

A1: Can you briefly describe the operational objectives of your respective work area?

____

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A2: What process data or variables do you monitor during operation?

Monitored variables (*e.g. flue gas temperature, efficiency*)	**Target value**	**Operation value**	**Units** **e.g.** °C	**How often is the target value met?** Scale: 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often & 5 = Always

A3: Are records kept of all

-Monitored data observations?	Yes:	☐	Maybe	☐	No	☐
-Corrective measures?	Yes:	☐	Maybe	☐	No	☐
-Subsequent actions were taken?	Yes:	☐	Maybe	☐	No	☐

A4: What are the primary causes of variations in the monitored variables?

____

____

____

A5: Is there a relationship between the monitored variables and energy usage?

A6: What variables are currently unmeasured, which you feel are important to the energy-efficient operation of your unit?

Section B: Operational Data

Department	**Operational metrics**	**Steady-state target or operating value**	**Units** *(e.g. °C)*	**Comments**
Extraction	Sugarcane throughput			
	Sugarcane fibre content			
	Dissolved solids content in bagasse			
	Bagasse ash content			
	Bagasse moisture content			
	Re-absorption factor			
	Imbibition water flow % cane fiber rate			
Evaporation	Syrup DS content			
	How often are the evaporator vessels cleaned?			
Crystallization	DS content of A massecuite			
	DS content of B massecuite			
	DS content of C massecuite			
	Operating pressure in pan A			
	Operating pressure in pan B			
	Operating pressure in pan C			
Boiler	Flue gas temperature			
	Flue gas oxygen concentration			

	Return condensate temperature			
Process Engineering	Total massecuite as m^3 per ton DS content in mixed juice			
	Cold-water used as % of boiler feedwater			
	How is the boiler efficiency determined during operation? (*please provide the formula used*)			
	% Boiler efficiency			
	HP steam tonnes/tonne sugarcane			
	Amount of movement water used in raw sugar pans % massecuite			

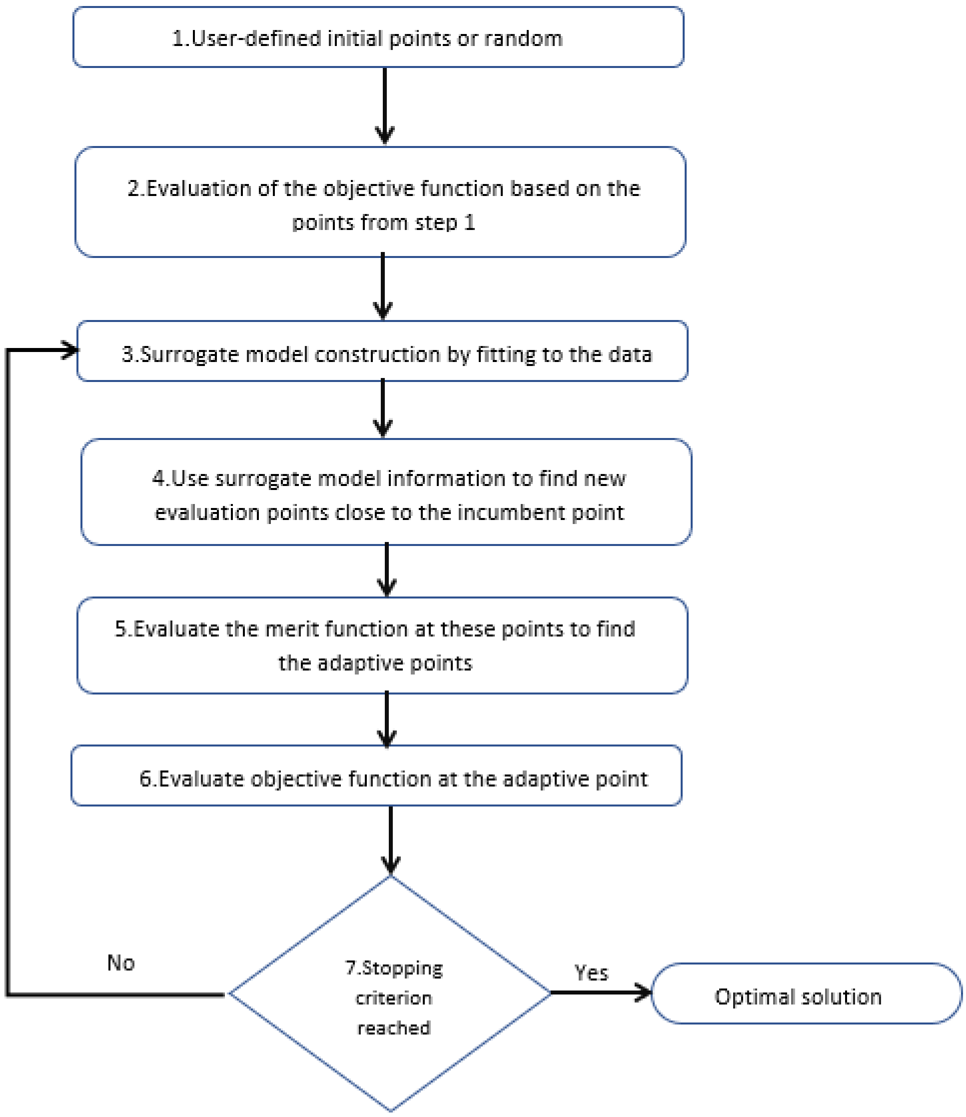
*HP-High Pressure

Appendix A2: MATLAB code for implementation of objective 2 and 3

Global optimization is used to search for global solutions to problems that contain multiple minima. A global minimum is a point where the objective function value is smaller than or equal to the value of all the feasible points of the problem. The global optimization toolbox in MATLAB includes solvers like the genetic algorithm, surrogate, and pattern search [1,2]. Each solver possesses different search characteristics; hence it is considered essential to select a solver that is best tailored for the defined optimization problem. Genetic algorithms and pattern search can handle all types of constraints while the surrogate optimizer only handles bound constraints. Based on the literature review, for non-smooth optimization problems, pattern search and surrogate optimization have been shown to converge to a local and global optimum, respectively while there is no proven convergence for genetic algorithms. In this regard, both pattern search and surrogate optimization were tested for a simplified study problem involving 4 CVs namely the DS contents of syrup and all the 3 massecuite streams from the cooling crystallizers. The pattern search optimizer provided an objective function value of US$8798/hr while the surrogate optimization provided a value of US$8803/hr. Therefore, by comparison of these two, it can be argued that the surrogate optimization algorithm can attain a global/best optimum solution (maximum net-revenue) compared to pattern search. Furthermore, pattern search took approximately 90 mins to converge to a solution while surrogate optimization only took 25 minutes. Considering the ability of surrogate optimization to converge to a global optimum while providing relatively good computation speeds, it was chosen for use in this study.

Surrogate optimization algorithm summary

Surrogate modeling is useful for computationally expensive, black box, and global optimization problems [3]. The objective function need not be smooth and although it can handle different types of variables, it works best with global optimization problems that have continuous variables [3]. Due to the black-box nature of the objective function to be minimized, derivatives are not available. Hence, surrogate models are constructed instead and used as the computationally cheap approximation of the objective function. Surrogate models can be constructed by either interpolation (kriging and radial basis function) or non-interpolation (polynomial regression) methods [4]. Kriging and radial basis functions interpolate the data points, which means they pass exactly through the response value. On the contrary, non-interpolation methods only approximate the data without necessarily having to pass through the data points [4]. If enough data points are provided, surfaces produced by interpolation can accurately represent complex data. The figure below illustrates the steps involved in a general surrogate optimization algorithm.



Typical steps in a surrogate optimization algorithm

Step 1 and 2: Surrogate optimization algorithm in MATLAB employs the user-provided initial points (if any) and quasi-random points which fall within the bounds of the problem variables for the evaluation of the computationally expensive objective function [4].

Step 3: A surrogate model of the objective function is then generated by interpolating a radial basis function through these points, such that the $s(x) = f(x) + e(x)$, where s(x) is the surrogate model prediction at x, f(x) the computationally expensive objective function value at x and e(x) the error term.

Step 4: During the optimization procedure, information attained from the surrogate model is used to guide the search for the minimum of the objective function by sampling several random points close to the incumbent point [4]. The incumbent point is the point with the smallest objective function value, this far.

Step 5 to 7: The solver uses these points to search for a minimum of a merit function which is a weighted combination of the scaled surrogate and the scaled distance of the existing search points [4]. The point with the minimum value of the merit function is called the adaptive point and is in turn used to evaluate the computationally expensive objective function (not the surrogate model) and update the surrogate [4]. These aspects of the surrogate optimization procedure enable it to attempt to strike a balance between exploration (searching for a global minimum) and speed (attaining this with minimal objective function evaluation). If the value of the objective function at the adaptive point is smaller than the previously attained value at the incumbent point, the adaptive point is deemed the new incumbent point for the next search. Therefore, the surrogate optimization algorithm alternates between the construction of the surrogate and the search for minimum phases. The specified maximum number of the objective function evaluation is the stopping criterion of the optimization algorithm.

Inputs and outputs of the surrogate optimization toolbox in MATLAB

The inputs of the surrogate optimization algorithm

i. Objective function-the file of the computationally expensive function (f(x) to be minimized. This function accepts a single input argument x which is a row vector and returns a scalar value.
ii. Constraints-the lower (lb) and upper bounds (ub) of the problem variables, x.
iii. Stopping criterion which sets the max number of function evaluation required.

The outputs of the surrogate optimization algorithm are:

i. The minimizing points (x) of the objective function
ii. The minimum value of the objective function (fval)

iii. An integer provides the reason for the optimization termination (exitflag).
iv. A structure describing the optimization procedure (output).
v. A structure (trials) of all the evaluated points (trials. X) and the corresponding objective function values (trials. Fval).

Optimization example based on surrogate optimization

Objective function definition

The defined objective function is the net operating revenue (J) which considers the prices of the raw materials and the value of the products in a sugarcane mill. Therefore, the aim is to maximize net income. However, to achieve this aim in a minimization algorithm the objective function is set as the negative of the net income, thus -J=Expenditure- Revenue.

The following prices in $/tonne were used in the present study:

Sugar=365; C-molasses=194.90; surplus bagasse=13.75; sugarcane=17.45; milk of lime consisting of 10% lime=8.5.

Decision variables and constraints

Four decision variables are considered for the minimization of the defined objective function in this example. The considered decision variables and their dimensions are shown in the table below.

The lower and upper bounds of the decision variables

Stream	**Bounds**		**Units**
	Lower	Upper	
Syrup	60.00	72.00	% Dissolved solids in syrup
A-massecuite	88.00	92.00	% Dissolved solids in massecuite A
B-massecuite	90.00	94.00	% Dissolved solids in massecuite B
C-massecuite	92.00	96.00	% Dissolved solids in massecuite C

The following options were set to:

i. Display in the command window for each iteration; the number of function evaluations, cumulative solver time, lowest, and current objective function.
ii. Plot the objective function value at each iteration, the algorithm phase, and the best value found for each iteration and overall.

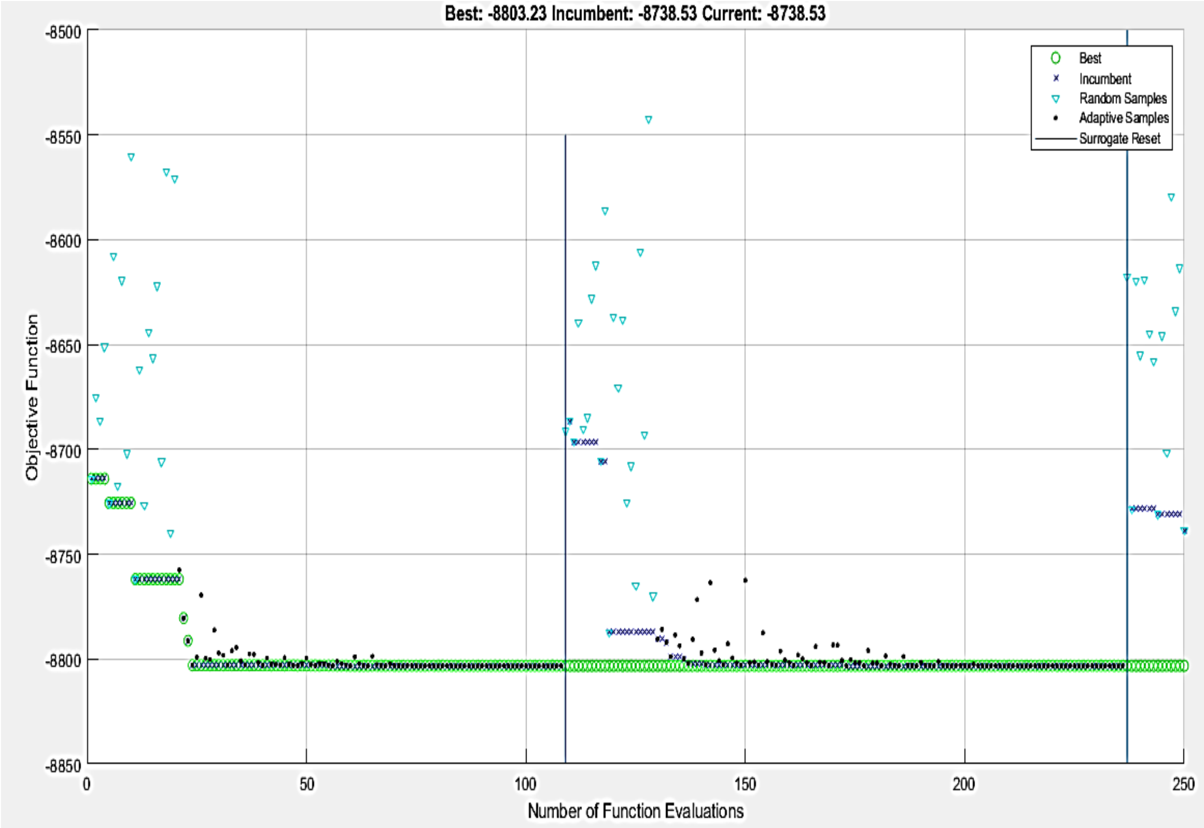
Example code for set-point optimization using surrogate optimization

```
%% Specifying the plant and stream location of the decision variables

tag.plant={'ext_evaporation','ext_crystallization','ext_crystallizat
ion','ext_crystallization'};

tag.stream = {'final_syrup_DS','DS_PANA','DS_PANB','DS_PANC'};

model_input = funcSM_input; %sugarcane mill model

% Objective function to be minimised

ObjectiveFunction = @(x) funcObjective (x, tag, model_input);

% Constraints

lb = [60 88 90 92]; % Lower bound

ub = [72 92 94 96]; % Upper bound

%Surrogate optimization

options=optimoptions('surrogateopt','Display','iter','PlotFcn',
@surrogateoptplot, 'MaxFunctionEvaluation',250);
[x,fval,exitflag,output,trials]=surrogateopt(ObjectiveFunction,lb,ub
,options);
```

The optimization results are interpreted to provide some details on the optimization steps and to assess whether the maximum number of function evaluations specified is adequate since it is the stopping criterion for optimization.

Plot interpretation

Below is the plot of the surrogate optimization steps which took place before the termination of the algorithm after 250 function evaluations. The plot is described from the first function evaluation point.



A plot illustration of the surrogate optimization steps at each objection function evaluation

i. Since no initial points were provided for this run, the light blue inverted triangles represent the quasi-random points generated within the bounds set for the decision variables. The objective function is evaluated at these points. The response values of the objective function at these points are used to construct the surrogate models.

ii. The incumbent point of the surrogate model is found just after the 20th function evaluation.

iii. Sample points are generated in a pseudo-random sequence around the incumbent point and these are the points used to evaluate the merit function, hence they are not represented in the plot. The points which provide the minimum merit function value are called adaptive points and are represented by the black dots. These are the points used to evaluate the computationally expensive objective function and the green circles indicate the best (lowest) objective function values found in each iteration.

iv. Close to the 30th to just after the 100th evaluation of the objective function the algorithm is stuck in a local minimum of approximately -8803.

v. The surrogate resets as represented by the blue vertical line near the 110th function evaluation. The algorithm again goes through the surrogate construction and search for minimum phases.

vi. By zooming in near the 150th function evaluation a dark blue cross with a green circle is observed indicating the new incumbent point which is the best since the surrogate reset. This incumbent point is at the same value of -8803 as the previous local minimum before the reset.

vii. The algorithm resets again at the 235th evaluation but is halted in the surrogate construction phase. This is because the maximum number of function evaluations is reached.

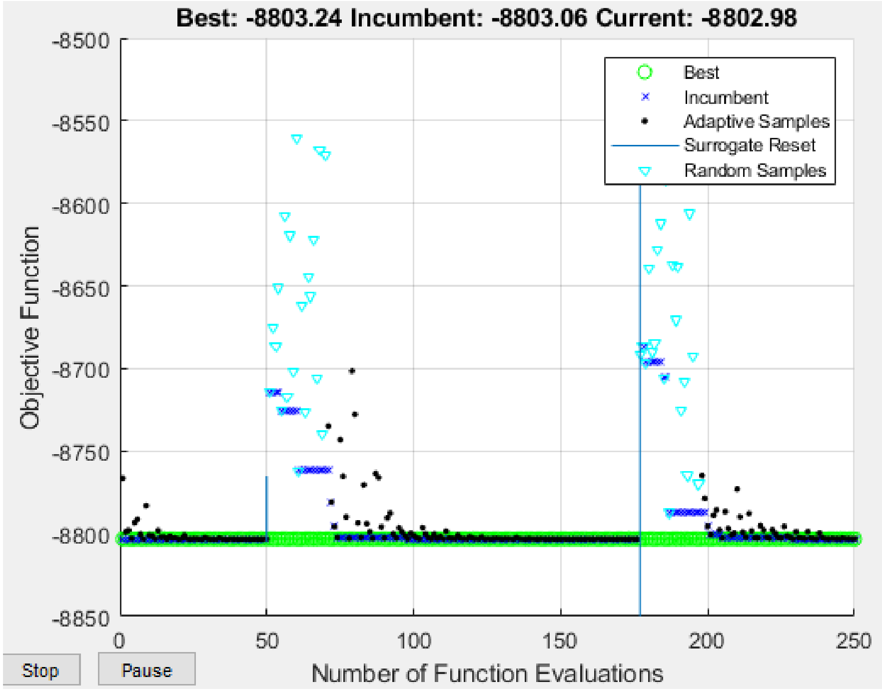
Therefore, to check if there would be any change in the minimum value found this far of -8803, additional function evaluation was set starting from the previously evaluated points. This was achieved by setting the structure, ‘trials’ as the initial points for use in the construction of the surrogate. Trials consist of the evaluated points (matrix with 250 rows and 4 columns) and the corresponding objective function values as a column vector.

The code used for the additional function evaluations is:

Options.InitialPoints=trials;

```
[x,fval,exitflag,output,trials]=surrogateopt(ObjectiveFunction,lb,ub
,options);
```

Below is the obtained surrogate plot. Again, the algorithm converged to the objective function value of -8803. Therefore, this appears to be the attained global minimum value of the defined objective function and it can thus be concluded that the maximum number of objective function evaluations is sufficient.



The plot of the additional 250 objective function evaluations based on the previously evaluated points

A similar approach was done for all the 14 CVs considered for the dissertation study and the surrogate optimizer was shown to converge to a global optimum after 350 function evaluations. To ensure that these standards are preserved for all the planned 5000 optimization runs, the number of maximum function evaluations was set to 500. In addition to speed up the computation times, parallel computing was utilized. More specifically the *spmd* function in MATLAB 2019b was used to execute the optimization code in parallel on workers of the parallel computing pool. The code used for the full optimization study involving all the 14 CVs comprises of two parts. Firstly the running of all the external process disturbances in the sugarcane mill model to extract a new model input structure (D) and secondly the optimization of the objective function at randomly sampled market prices and process model input state for given external process disturbances.

Sensitivity analysis code at randomly sampled values of the process disturbances

```
%% Iterating through the process disturbances random samples
Disturbances_RSamples=struct
('CaneFlow',random.flow,'CaneFibre',random.canequality
(:,1),'CaneSucrose',random. quality (:,2),'CanePol',random.
quality(:,3),'CaneDS',random.quality(:,4),'AirTemp',random.climate(:
,1),'AirHumidity',random.climate (:,2));
```

```
ncols = length(fieldnames (Disturbances_RSamples));
rfieldnames = fieldnames (Disturbances_RSamples)';
nrows = length (Disturbances_RSamples.(rfieldnames{1}));
Process_disturbances = zeros(nrows, ncols);

     for ifield = 1:ncols
         Process_disturbances(:, ifield) =
     Disturbances_RSamples.(rfieldnames{ifield});
     end

          for k = 1:nrows
              Process_disturbances(k,:);

% Inserting the disturbance random sample combinations to the model
inputs
tag.plant  = {'ext_diffusion',
'ext_diffusion','ext_diffusion','ext_diffusion','ext_diffusion',
'ext_drying','ext_drying'};
tag.stream =
{'F_CANE','fibre_CANE','suc_CANE','pol_CANE','brix_CANE',
'T_DAI','phi_DAI'};

% Running the sugar mill model at randomly sampled values of the
process disturbances and saving the new model input structure as D.
model_input = funcSM_input;
D(k)=funcD(Process_disturbances(k,:), tag,model_input);
disp (k);
end
```

Surrogate optimization code for dissertation study

% Specifying the process unit (plant) and stream allocation of the 14 decision variables

```
tag.plant={'ext_evaporation','ext_crystallization','ext_crystallizat
ion','ext_crystallization','ext_diffusion','ext_crystallization',
'ext_crystallization','ext_clarification','ext_clarification','ext_c
larification','ext_evaporation','ext_crystallization','ext_crystalli
zation','ext_crystallization'};
```

```
tag.stream={'final_syrup_DS','DS_PANA','DS_PANB','DS_PANC','T_PWH','
Brix_REMC','T_REMC','T_MJ1','T_MJ2','T_MJ3','feed_temperature','T_PA
NA','T_PANB','T_PANC'};

load (Disturbances.mat')
load('MarketPrice.mat')

nrows=length(D);
OptimizationResults=zeros(nrows,15);
trialruns=cell(nrows,2);

     spmd
     mkdir(sprintf('worker%d', labindex));
     copyfile('sm_input_data.mat',sprintf('worker%d/',labindex));
     copyfile('vsmm.exe',sprintf('worker%d/',labindex));
     copyfile('sm_output_data.mat',sprintf('worker%d/',labindex));
     cd(sprintf('worker%d', labindex));
     end
for n=1:nrows
model_input = D{n};
cost=row_prices(n,:);
disp(n);
ObjectiveFunction = @(x) funcOptimizationOctober(x, tag,
model_input,cost);
lb = [57 90 92 93 65 60 60 70 91 102 110 61 61 61]; % Lower bound
ub = [72 94 96 98 84 80 80 85 97 108 116 74 74 74]; % Upper bound
options=optimoptions('surrogateopt','Display','iter','UseParallel',
true,'MaxFunctionEvaluation',500);
[x,fval,exitflag,output,trials] =
surrogateopt(ObjectiveFunction,lb,ub,options);
OptimizationResults(n,:)=[x fval];
trialruns{n}=trials;
save('Optimization_ForAllDisturbances','trialruns','OptimizationResu
lts')
 end
```

References

1. Mathworks documentation: What is Global optimisation?
2. Mathworks documentation: Global optimization toolbox solver characteristics
3. Mathworks documentation: Surrogate optimization
4. Müller, J. & Shoemaker, C.A. Influence of ensemble surrogate models and sampling strategy on the solution quality of algorithms for computationally expensive black-box global optimization problems. J Glob Optim (2014) 60: 123-144.

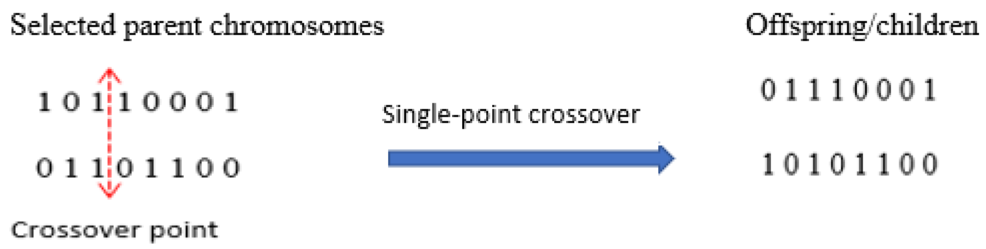
Appendix A3: MATLAB code for implementation of objective 4

Genetic algorithms description

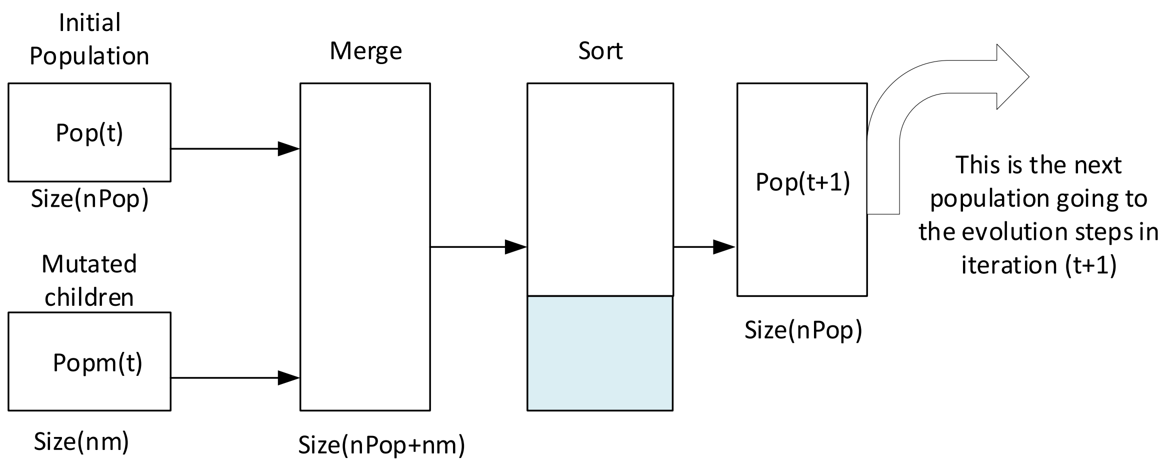
Genetic algorithms (GAs) are population-based stochastic methods for solving optimization problems the optimization of problems. The mathematical techniques used in genetic algorithms are developed based on the biological principles of natural selection and genetics. Genetic algorithms have been successfully used in previous studies to solve sensor placement optimization problems as they can handle integer bound constraints and problems involving large process systems. The implementation code for GAs has 4 parts namely: initialization, selection, crossover, and mutation. Initialization of the genetic algorithm is done by randomly selecting a population of chromosomes of the size specified by the user. The generated chromosomes are used to evaluate the objective function. The initial population is constructed once and then subjected to the genetics operators of selection, crossover, and mutation operators. In this regard, the robustness of the initial population that is constructed is important and for these reasons, brute force was used for this dissertation.

For parent selection, two methods are commonly used namely tournament selection and roulette wheel. For the tournament selection strategy, no arithmetic computation is required. Instead, several random combinations are generated, and their objective function values are evaluated and compared. The combination with the best objective function value is selected as a parent. In roulette wheel selection, the proportion of each measurement combination objective function value to the sum of the objective function values of all combinations in the population is computed. These proportions are used to partition the roulette wheel and thus every sector is proportional to the probability of a combination being selected as a parent for reproduction. The roulette wheel approach was used in this study.

For the crossover, a crossover probability is specified and applied to all the selected parent chromosomes. The probability is generally close to 1 such that most parents will exchange their genes. For this study, three types of crossover functions were selected namely single-point, double-point, and uniform crossover, and their functions were created in such a manner that for each iteration a method for use is randomly selected. An example of a single point cross-over is provided below.



The operations of reproduction and crossover may reduce the population diversity, and thus, the chromosomes (sensor combinations) can tend to become significantly similar over several generations. Therefore, perturbations are introduced into the population to protect against the premature convergence to a non-optimal solution. Mutation serves the function by replacing a gene (sensor location) in a chromosome (sensor combination) at a randomly selected location. The mutation probability is usually specified as a small value. The mutated offsprings are evaluated against the objective function. As shown below, the mutated population is merged with the initial population, sorted based on the objective function values and the population size (nPop) for the second generation is chosen. This strategy ensures that for each iteration (MaxIt) only the best nPop combinations in the initial population and mutated population are chosen.



Merging the initial population with mutated children, sorting based on best function value, and taking the top nPop size combinations for the next iteration.

In this study, a restriction has been declared on all the functions created for GA to ensure the number of 1s in the row vector is equal to the number of measurements or sensors required. For example, if 3 measurements are required amongst 10 candidate measurements, and the following combinations are chosen as parents 1000101000 and 0001001010 which represent that three sensors are placed at positions 1, 5, and 7 and positions 4,7, and 9. Through single-point crossover say at position 5 the following combinations are attained 1000101010 and 0001001000. However, these chromosomes have violated the requirements of the study to choose only three measurements out of the 10 as they have 4 and 2 measurements, respectively. For these reasons, it has been considered necessary to declare a restriction on the functions for population creation, parent selection, crossover, and mutation subject to the number of measurements required.

Implementation of optimal sensor placement MATLAB code based on Gas

Initial population construction MATLAB code

```
N = 1000;  % Number of random samples to generate(number increased in case
of duplicates
n = 234;    % Number of candidate measurements
z = 41;     % Number of CVs or measurements required
r = [ones(1,z) zeros(1,n-z)];

% Restriction to ensure a maximum of 1 sensor is allocated per variable
% List of candidate sensors from which only one can be chosen
constraints{1}=[1  79 157];
constraints{2}=[2    80 158];
constraints{3}=[3    81 159];
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constraints{6}=[6    84 162];
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constraints{32}=[32   110 188];
constraints{33}=[33   111 189];
constraints{34}=[34   112 190];
```

```
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constraints{36}=[36   114 192];
constraints{37}=[37   115 193 ];
constraints{38}=[38   116 194];
constraints{39}=[39   117 195];
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constraints{46}=[46   124 202];
constraints{47}=[47   125 203];
constraints{48}=[48   126 204];
constraints{49}=[49   127 205];
constraints{50}=[50   128 206];
constraints{51}=[51   129 207];
constraints{52}=[52   130 208];
constraints{53}=[53   131 209];
constraints{54}=[54   132 210];
constraints{55}=[55   133 211];
constraints{56}=[56   134 212];
constraints{57}=[57   135 213];
constraints{58}=[58   136 214];
constraints{59}=[59   137 215];
constraints{60}=[60   138 216];
constraints{61}=[61   139 217];
constraints{62}=[62   140 218];
constraints{63}=[63   141 219];
constraints{64}=[64   142 220];
constraints{65}=[65   143 221];
constraints{66}=[66   144 222];
constraints{67}=[67   145 223];
constraints{68}=[68   146 224];
constraints{69}=[69   147 225];
constraints{70}=[70   148 226];
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constraints{72}=[72   150 228];
constraints{73}=[73   151 229];
constraints{74}=[74   152 230];
constraints{75}=[75   153 231];
constraints{76}=[76   154 232];
constraints{77}=[77   155 233];
constraints{78}=[78   156 234];

pop = zeros(N, n);% Initialize possible options

for i = 1:N
disp(i)
    pop(i,:) = funcGenerateSample(r, constraints);% Call function to
generate random, valid sample

end

pop = unique(pop, 'rows') ; % Remove identical samples from the list

function pop = funcGenerateSample(r, constraints)

% Function to generate a random sample and check that it is valid
```

```
invalid = 1;

while invalid

    pop = r(randperm(length(r)));% Generate random permutation

    invalid = 0;% Assume the permutation is valid

    for i = 1:length(constraints)% Check each constraint

        if sum(pop(constraints{i})) > 1 % Verify if constraint is violated

            invalid = 1; % If violated, mark as invalid

            continue % and terminate checking

        end
    end

end

end
```

The objective function definition for optimal sensor placement

The objective is to select an optimal sensor placement that results in maximum factory revenue by minimizing the loss in revenue due to the implementation of self-optimizing control and minimizing the total instrumentation cost. The procedure for the exact evaluation of the loss due to disturbances and measurement errors can be summarised as follows:

i. Definition of a scalar objective function, $\boldsymbol{J}(\boldsymbol{u},\boldsymbol{d})$ for quantifying operation.
ii. Optimization at nominal d value (d^*) using the remaining degrees of freedom.
iii. Specification of the magnitudes of d and n, to get $\boldsymbol{W_d}$ and $\boldsymbol{W_n^y}$.
iv. Computation of second partial derivatives, $\boldsymbol{J_{uu}}$ and $\boldsymbol{J_{ud}}$ and the matrices $\boldsymbol{G^y}$ and $\boldsymbol{G_d^y}$.
v. Calculation of the optimal CV sensitivity to d, **F**.
vi. Determination of the optimal **H** matrix for each measurement combination to get $\boldsymbol{G^c}$ and $\boldsymbol{G_d^c}$.
vii. Calculation of the matrix **M**, for each combination.
viii. Computation of the $\boldsymbol{L_{ave}}$ for each GA selected sensor combination (chromosomes).

The total cost for the sensor combination J_{sc} is calculated as shown below where N_c represents the total number of measurements considered for optimal sensor placement.

$$Total\ sensor\ cost, J_{sc}\ (US\$/hr) = \sum_{i=1}^{N_c} \frac{Sensor\ cost}{Sensor\ life\ span}$$

In this regard, the overall objective function J_T , for optimal sensor placement is denoted as:

$$J_T = \min_{C \in y^{all}} L_{ave} + J_{sc}$$

The function for the overall sensor placement is coded in MATLAB 2019b and saved as "*myfunction*".

Optimal sensor placement code based on genetic algorithms

```
%% Problem Definition

CostFunction=@(x) myfunction(x);% Objective function for optimal
sensor placement
nVar=234; % Number of Decision Variables
VarSize=[1 nVar];% Decision Variables Matrix Size

%% GA Parameters

MaxIt=100; % Maximum number of iterations
nPop=500; % Population Size
pc=0.8; % Crossover Percentage
beta=8; % selection pressure
nc=2*round(pc*nPop/2); % Number of Offsprings
mu=0.2;% Mutation Rate


%% GAs Initialization

empty_individual.Position=[];%Empty templates for sensor placement
and cost
empty_individual.Cost=[];

pop=repmat(empty_individual,nPop,1);
bestsol.Cost=inf;

for i=1:nPop

    load Initialpop.mat initpop;

    pop(i).Position= initpop(i,:);% chromosome or measurement
combination

 % Evaluate the cost function at a given position (sensor
combination)

   pop(i).Cost=CostFunction(pop(i).Position);

    %Compare Solution to Best So Far

   if pop(i).Cost<bestsol.Cost
     bestsol=pop(i);
```

```
    end

end


bestcost=nan(MaxIt,1);%Preallocating an empty template for best
costs per iteratiion
```

%% Main loop: Starting of the evolutionary steps of selection, crossover & mutation of the children at a specified rate.

```
for it=1:MaxIt


    %Selection of probabilities for Roulette wheel selection

    c=[pop.Cost];
    avgc=mean(c);
        if avgc~=0

            c=c/avgc;
        end
    probs=exp(-beta*c);

    popc=repmat(empty_individual,nc/2,2);% children pop empty template
```

%% Crossover

```
    for k=1:nc/2


      p1=pop(RouletteWheelSelection(probs)); %Select parent
      p2=pop(RouletteWheelSelection(probs));

      [popc(k,1).Position,popc(k,2).Position]=SinglePointCrossover(p
      1.Position,p2.Position); %Performing crossover

    end

    popc=popc(:); %Converting popc to a single column matrix
```

%% Mutation

```
    for l=1:nc


       popc(l).Position=Mutate(popc(l).Position,mu);% mutation

       popc(l).Cost=CostFunction(popc(l).Position);%evaluate function

        if popc(l).Cost<bestsol.Cost

            bestsol=popc(l); %Compare solution to best found
```

```
        end
    end
%% Merge and Sort population
   pop=SortPopulation([pop;popc]);
%Remove extra individuals from the population
   pop=pop(1:nPop);
   bestcost(it)=bestsol.Cost;% Update best cost of iteration
  %Display iteration information
   disp(['Iteration' num2str(it) ': Best Cost = 'num2str(bestcost(it))])
   GAresults=bestsol;
end
%% Results and plots
figure;
plot(bestcost,'LineWidth',2);
xlabel('Iterations');
ylabel('Best Cost');
grid on;
```

Appendix A4: Numerical evaluation of partial derivatives

The sugarcane mill model was developed for design purposes hence in some instances output process variables were considered as input variables and the manipulated variables as the output variables.

Model inputs: All disturbances (d) and some output variables y which are represented as y_i.

Model outputs: manipulated variables,u_o and some output process variables y_o.

The number of variables: $Nu_o = 41; Ny_o = 40; Ny_i = 38; Nd = 7;$

To allow for the computation of the first and second partial derivatives the following approach was used:

$$\boldsymbol{G_d^y} = \left[\frac{\Delta \boldsymbol{y_o}}{\Delta \boldsymbol{d}} \; ; \; \frac{\Delta \boldsymbol{y_i}}{\Delta \boldsymbol{d}}\right]$$

$$\boldsymbol{G^y} = \left[\frac{\Delta \boldsymbol{y_o}}{\Delta \boldsymbol{u_o}} \; ; \; \frac{\Delta \boldsymbol{y_i}}{\Delta \boldsymbol{u_o}}\right]$$

Steps used to get:

i. $\frac{\Delta \boldsymbol{y_o}}{\Delta \boldsymbol{d}}$ - Small deviations in d are done and the effect on y_o is observed.

ii. $\frac{\Delta \boldsymbol{y_i}}{\Delta \boldsymbol{d}}$ - Small deviations are made to d and y_i. The resultant effect on u_o is used to compute $\frac{\Delta \boldsymbol{y_i}}{\Delta \boldsymbol{d}}$ as $\frac{\Delta \boldsymbol{y_i}}{\Delta \boldsymbol{d}} = \frac{\Delta u_o}{\Delta d} * \left(\frac{\Delta u_o}{\Delta y_i}\right)^{-1}$.

iii. $\frac{\Delta \boldsymbol{y_o}}{\Delta \boldsymbol{u_o}}$ -Small deviations are made to y_i while the effect on y_o and u_o is observed. From these observations, $\frac{\Delta \mathbf{y_o}}{\Delta \mathbf{u_o}} = \frac{\partial \mathrm{y_o}}{\partial \mathrm{y_i}} * \left(\frac{\partial \mathrm{u_o}}{\partial \mathrm{y_i}}\right)^{-1}$.

iv. $\frac{\Delta \boldsymbol{y_i}}{\Delta \boldsymbol{u_o}}$ - Small deviations in y_i are done and the observed effect on u_o is used to get $\frac{\Delta \boldsymbol{y_i}}{\Delta \boldsymbol{u_o}} = \left(\frac{\Delta u_o}{\Delta y_i}\right)^{-1}$.

The same strategy was used for getting J_{uu} by observing changes in J and each combination of two manipulated variables u_o with each d deviation. For J_{ud} changes in J and u_o with each d deviation are considered.

Appendix B: Supplementary information

Set-point optimization for plant-wide control of a sugarcane mill under process and market prices disturbances: Energy and Economic Perspectives

Subtitle: Supplementary Online Material

Authors: Thobeka Mkwananzi; Mohsen Mandegari[5]✉ ;Tobi M. Louw; Lidia Auret and Johann F. Görgens

Department of Process Engineering, University of Stellenbosch, Private Bag X1, Matieland, 7602, South Africa

[5]✉ Correspond author: M Mandegari, Phone: +27 21 808 9485; Fax: 27 21 808 2059; E-mail: mandegari@sun.ac.za

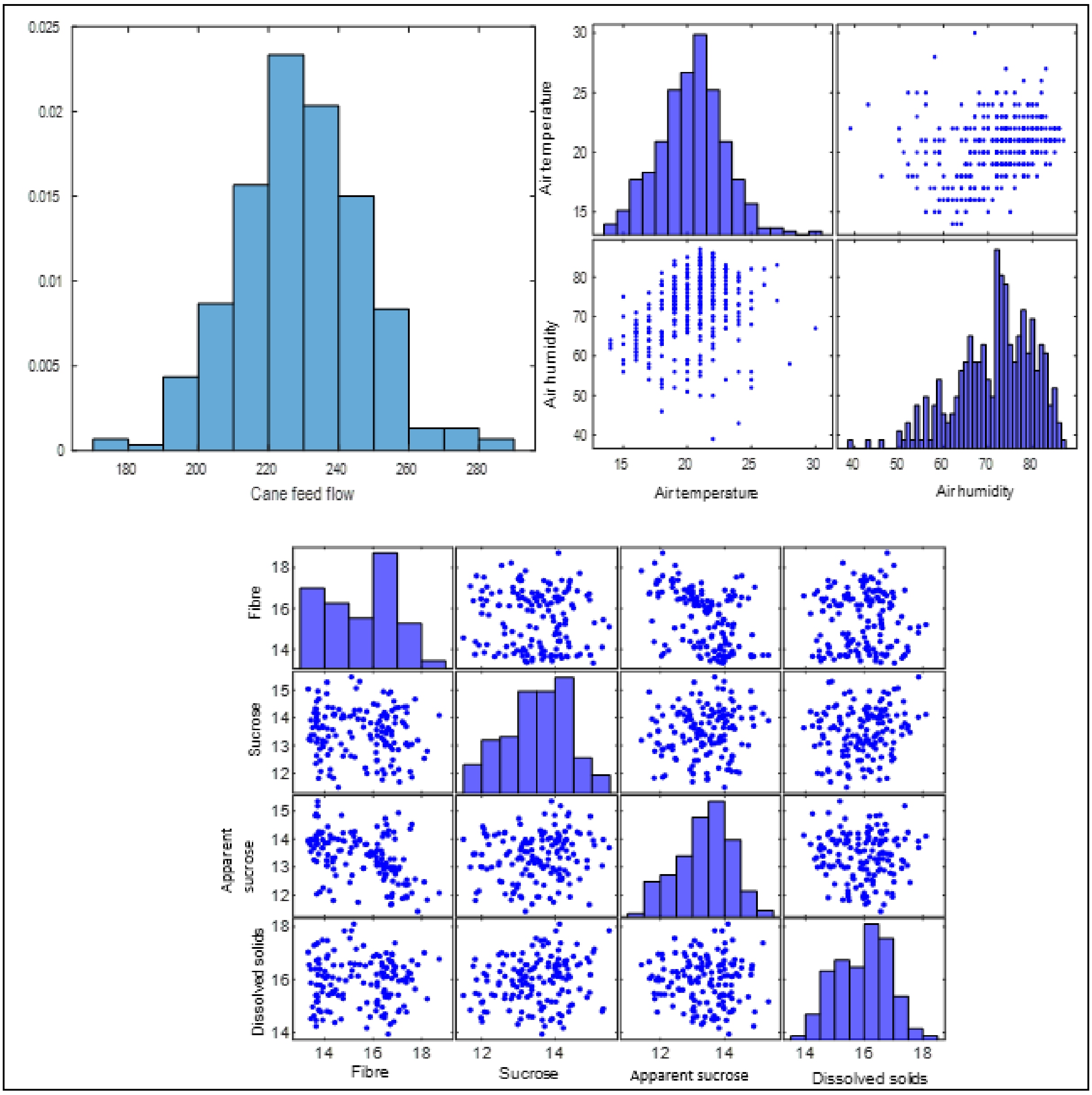
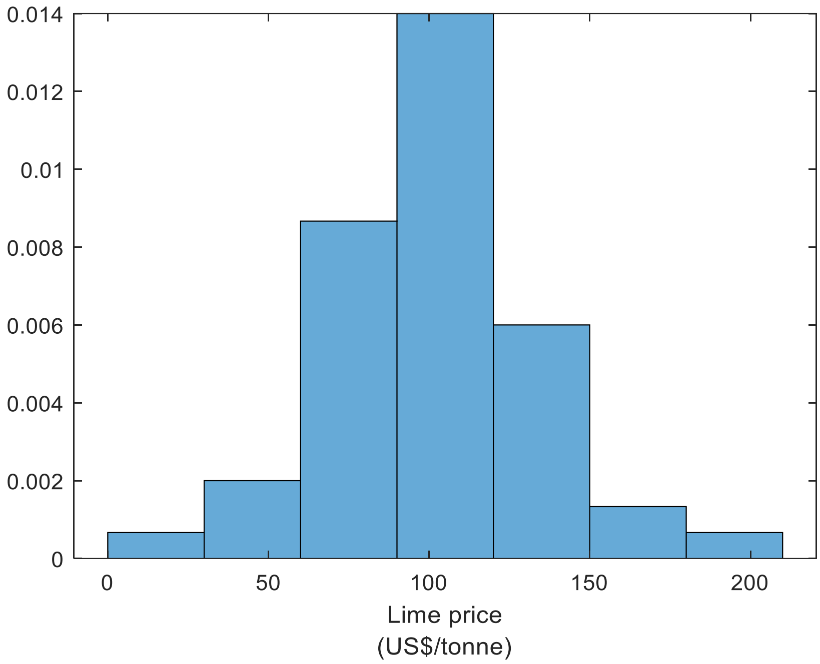
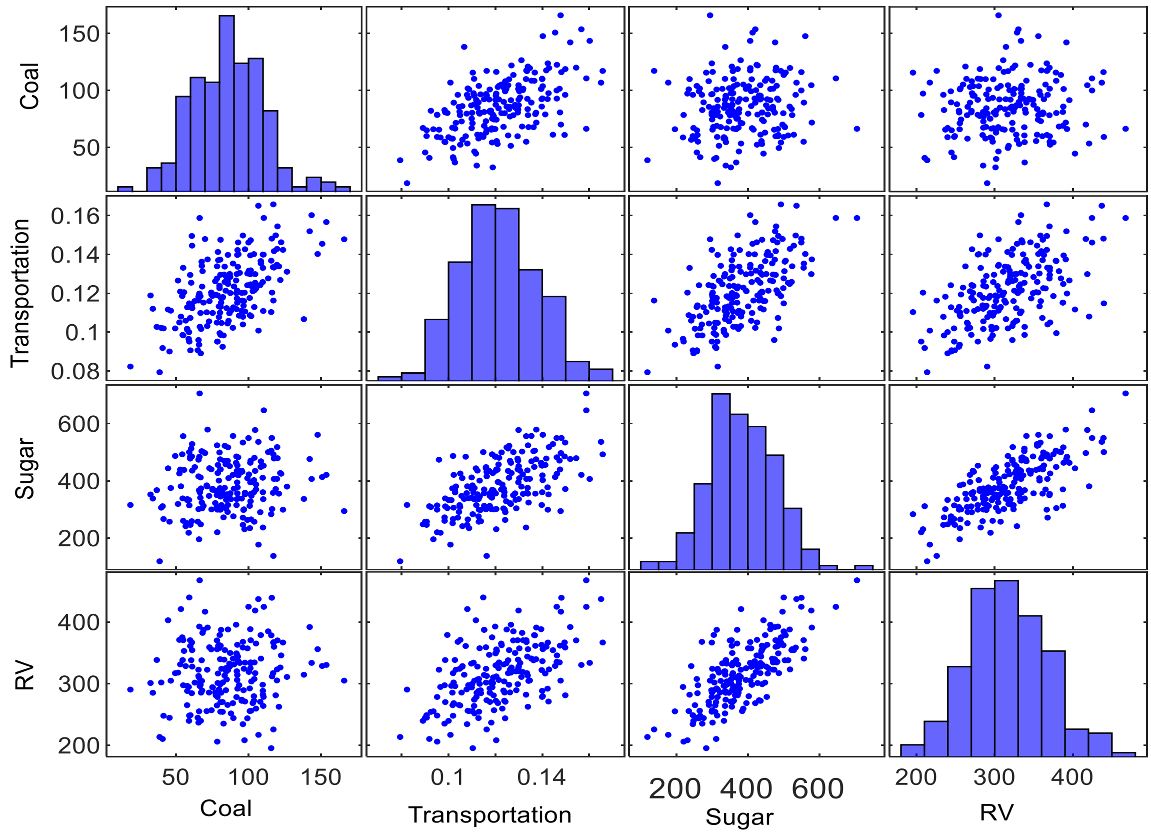


Figure S-8-1: Histogram plots for sugarcane flow and marginalized histogram and scatter plots for bivariate (air temperature and humidity) and multivariate distributions (sugarcane quality variables)



(I)



(II)

Figure S-8-2: Histogram plots for the lime price (I) and marginalized histogram and scatter plots for coal, transportation, sugar, and recoverable value (RV) prices (II).

Table S-8-1: Specifications of the three computers used in this study and their corresponding run times for a single optimization task

Category	**Computer 1**	**Computer 2**	**Computer 3**
Central processing unit (CPU)	1.60 GHz1 with 1TB solid-state drive	3.33GHz (2 processors)	2.89 GHz (12 processors)
Random Access Memory (RAM)	8GB	32 GB	32 GB
Serial optimization time (minutes)	97	75	70
Parallel optimization time(minutes)	40-50	20-30	25-30
Number of parallel workers	6	6	12

Table S-8-2: The percentiles and summary statistics for the external process variables and market prices

Disturbances	**Units**	**Percentile values**			**Parametric statistics**	
		5^{th}	50^{th}	95^{th}	Mean	Variance/Covariance
External process variables						
Sugarcane flow	tonnes/hr	201.84	229.27	256.83	229.47	16.89^2
Sugarcane fiber	% cane	13.21	15.48	17.76	15.50	$\begin{bmatrix} 1.95 & -0.10 & 0.02 \\ -0.10 & 0.76 & 0.14 \\ 0.02 & 0.14 & 0.79 \end{bmatrix}$
Sugarcane sucrose		12.51	13.70	14.88	13.49	
Sugarcane DS		14.47	15.76	17.08	15.94	
Air temperature	℃	16.14	20.31	24.51	20.34	$\begin{bmatrix} 6.62 & 6.06 \\ 6.06 & 76.24 \end{bmatrix}$
Air humidity	%	61.30	73.27	85.65	71.54	
Market prices						
Lime	US$/tonne	52.06	93.11	134.37	93.41	25.28^2
Coal	US$/tonne	48.15	84.82	121.68	85.09	$\begin{bmatrix} 510 & 0.23 & 520 & 226 \\ 0.23 & 0.0003 & 1.18 & 0.55 \\ 520 & 1.18 & 10026 & 3793 \\ 226 & 0.55 & 3793 & 2632 \end{bmatrix}$
Coal transport	US$/km	0.099	0.12	0.15	0.12	
Raw sugar	US$/tonne	248.72	398.66	550.06	384.96	
Sugarcane	US$/tonne RV	230.04	316.86	403.07	317.53	

Appendix C: Supplementary Information

Optimal sensor placement for a typical sugarcane mill using self-optimizing control and genetic algorithms

Subtitle: Supplementary Online Material

Authors: Thobeka Mkwananzi; Tobi M. Louw; Lidia Auret; Mohsen Mandegari[6]✉ ; and Johann F. Görgens

Department of Process Engineering, University of Stellenbosch, Private Bag X1, Matieland, 7602, South Africa

[6]✉ Correspond author: M Mandegari, Phone: +27 21 808 9485; Fax: 27 21 808 2059; E-mail: mandegari@sun.ac.za

Table S-8-3: Nominal values for the disturbances and market prices used to define the steady-state operation

External process disturbances (d*)		
Stream	**Nominal value**	**Units**
Cane flow	250	tonnes/hr
Cane fiber content	15.06	%
Cane sucrose content	14.17	%
Cane dissolved solids content	16.41	%
RH-DAI (air humidity)	75.00	%
Market prices (P)		
Lime	93.41	US$/tonne
Coal	85.09	US$/tonne
Transportation	0.12	US$/km
Sugar	384.96	US$/tonne
Recoverable value	317.53	US$/ tonne RV
Sugarcane	41.55	US$/tonne

Table S-8-4: Optimal values for the manipulated variables at nominal values of the disturbances (d^*)

Manipulated variables, $\mathbf{u_{opt}}(\mathbf{d}^*)$			
Stream	**Optimal * (tonnes/hr)**	**Stream**	**Optimal * (tonnes/hr)**
SB1	21.20	REMC	1.55
SD1	4.75	WWA	3.03
SD3	14.25	WWB	0.05
SD5	2.20	WWC	1.54
SPW	1.20	SKA	12.49
IW	101.94	SKB	1.88
SDI	3.93	SKC	2.97
SDH	8.12	CWA1	8.74
LIM	7.21	CWB1	0.00
BGO	0.95	CWC1	4.67
SHP	11.08	CTP	609.50
SHS	7.15	CER	0.17
SHT	2.69	SER	0.06
WW	4.40	EXSS	0.33
S0	70.17	DA1	73.86
M	1501.54	DAI1	12.13
S1	47.11	DAI2	61.72
S2	31.23	BGB	37.46
CCF	4.63	WBM	5.64
SYRA	45.54	SBO	58.06
SYRM	2.11		

Table S-8-5: Optimal values for the controlled variables at nominal values of the disturbances (d^*). DS is the dissolved solids concentration.

Candidate controlled variables, $y_{opt}(\mathbf{d}^*)$			
Temperature streams	**Optimal * (°C)**	**Pressure streams**	**Optimal * (bars)**
PWH	65.00	SD2	2.01
DJ	59.53	SD4	2.01
SDH	106.96	SD6	2.01
MJ	63.22	PANA	0.15
MJ1	85.00	PANB	0.054
MJL	83.51	PANC	0.076
MJ2	97.00	**Concentration streams**	**Optimal * (mass fraction)**
MJ3	102.00	BAG water content	0.50
MJF	100.23	SUA water content	0.0008
CJ	99.75	BAG DS content	0.015
SHP	84.77	MJ DS content	0.14
SHS	106.96	MJL DS content	0.13
SHT	114.22	CJ DS content	0.13
SYR	60.29	FC sucrose content	0.023
L0	115.50	SYR DS content	0.72
L1	114.22	L1 DS content	0.18
M	25.00	L2 DS content	0.24
W	40.00	L3 DS content	0.31
SB2	121.21	L4 DS content	0.43
S0	121.21	PANA DS content	0.94
S2	105.91	MASA DS content	0.94
S3	84.60	MOLA DS content	0.75
S4	76.47	SUGA DS content	0.99
SEH	121.21	PANB DS content	0.95
MASA	56.22	MASB DS content	0.95
MASB	49.85	MOLB DS content	0.91
MASC	45.22	PANC DS content	0.93
REMC	79.56	MASC DS content	0.93
SKA	114.22	MOLC DS content	0.78
SKB	114.22	REMC DS content	0.80
SKC	106.96	SUA DS content	0.99
CWA2	59.54		
CWB2	52.73		
CWC2	52.00		
SUA	35.67		
DAH	80.00		

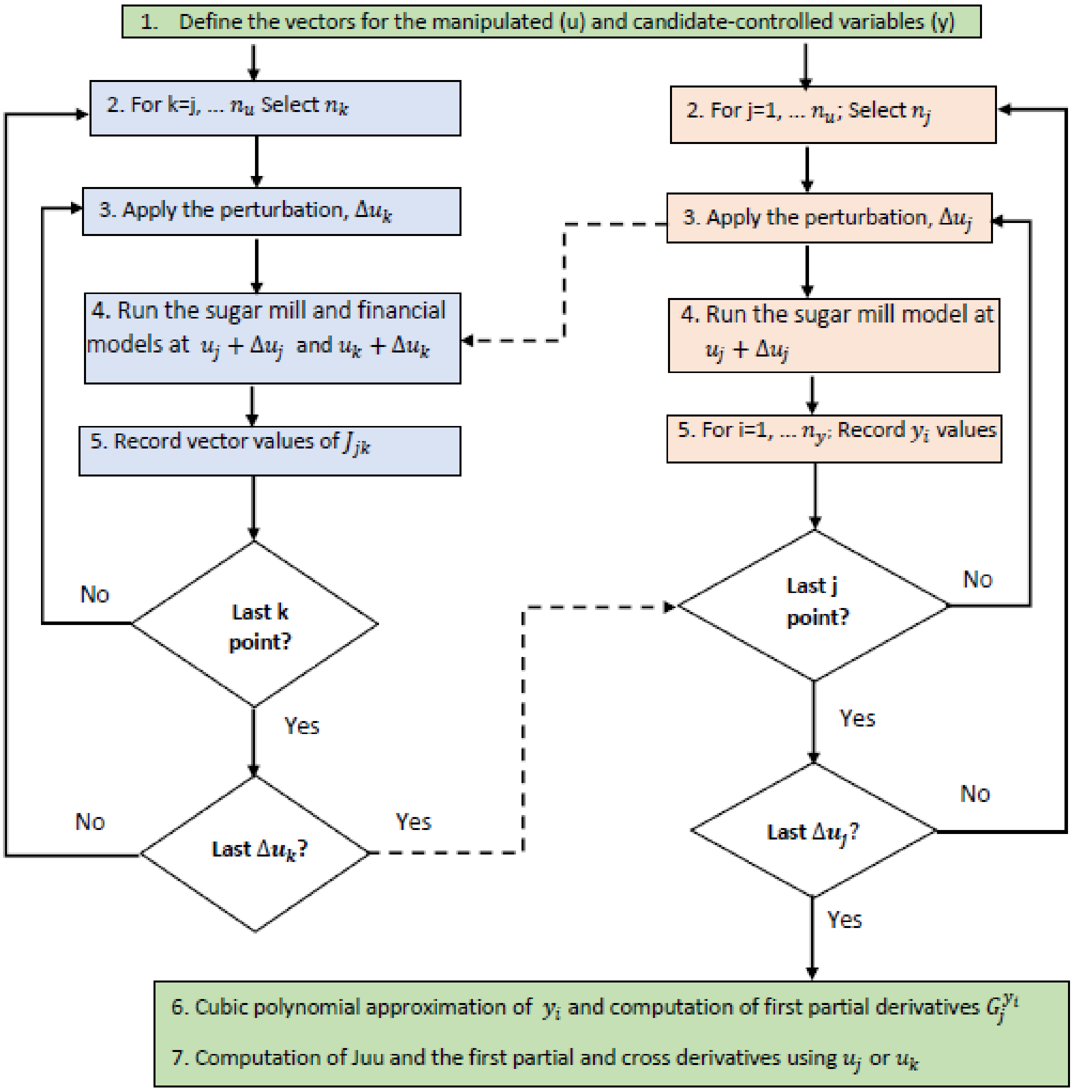


Figure S-8-3: Strategy used for getting the first partial derivatives G^y and G_d^y as well as the second partial derivatives J_{ud} and J_{uu}.

Table S-8-6: Sensor error and purchasing cost (with sensor life span considered)

Key	
	temperature
	pressure
	dissolved solids content
	moisture content

Candidate measurements	Typical sensors in sugarcane mills		Obtained from manufacturing companies			
	Sensor error	Sensor cost (US$/hr)	Sensor error	Sensor cost (US$/hr)	Sensor error	Sensor cost (US$/hr)
SB1	0.40%	0.0041	0.35%	0.0038	0.30%	0.0047
SD2	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SD4	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SD6	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
PWH	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MJ1	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MJ2	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MJ3	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
L0	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
W	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
SB2	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
PANA	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
PANB	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
PANC	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MASA	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MASB	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MASC	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
REMC	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
WK	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
SUAH	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
SUAD	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
DAH	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
T_EXSS	0.15 +0.2%	0.0033	0.3+0.5%	0.0035	0.1+0.0017	0.0040
CTW	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
SB1	0.3%	0.0168	0.04%	0.0791	0.17%	0.0479
SD2	0.3%	0.0168	0.04%	0.0791	0.17%	0.0479
SD4	0.3%	0.0168	0.04%	0.0791	0.17%	0.0479
SD6	0.3%	0.0168	0.04%	0.0791	0.17%	0.0479
P_EXSS	0.3%	0.0168	0.04%	0.0791	0.17%	0.0479
SB2	0.3%	0.0168	0.04%	0.0791	0.17%	0.0479
BAG water	0.10%	0.0407	0.05%	0.1158	0.08%	0.0783
SYR DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
PANA DS content	1.50%	0.3835	0.05%	0.3940	0.15%	0.4132
PANB DS content	1.50%	0.3835	0.05%	0.3940	0.15%	0.4132
PANC DS content	1.50%	0.3835	0.05%	0.3940	0.15%	0.4132
REMC DS content	1.50%	0.3835	0.05%	0.3940	0.15%	0.4132

SUAD moisture	0.05%	0.0407	0.01%	0.1158	0.03%	0.0783
SUAH moisture	0.05%	0.0407	0.01%	0.1158	0.03%	0.0783
DJ	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
SDH	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
MJ	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MJL	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
MJF	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
CJ	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SHP	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
SHS	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SHT	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SYR	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
L1	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
S0	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
S1	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
S2	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
S3	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
S4	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SEH	0.15 +0.2%	0.0033	0.3+0.5%	0.0028	0.1+0.0017	0.0036
SKA	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SKB	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SKC	0.15 +0.2%	0.0041	0.3+0.5%	0.0035	0.1+0.0017	0.0045
SBO	0.40%	0.0041	0.35%	0.0043	0.30%	0.0050
PANA	0,3%	0.0168	0.04%	0.0791	0.17%	0.0479
PANB	0,3%	0.0168	0.04%	0.0791	0.17%	0.0479
PANC	0,3%	0.0168	0.04%	0.0791	0.17%	0.0479
SBO	0,3%	0.0168	0.04%	0.0791	0.17%	0.0479
BAG DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
MJ DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
MJL DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
CJ DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
FC sucrose	1%	0.3835	0.05%	0.3940	0.15%	0.4132
L1 DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
L2 DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
L3 DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
L4 DS content	1%	0.3835	0.05%	0.3940	0.15%	0.4132
MASA DS content	1,5%	0.3835	0.05%	0.3940	0.15%	0.4132
MOLA DS content	1,5%	0.3835	0.05%	0.3940	0.15%	0.4132
MASB DS content	1,5%	0.3835	0.05%	0.3940	0.15%	0.4132
MOLB DS content	1,5%	0.3835	0.05%	0.3940	0.15%	0.4132
MASC DS content	1,5%	0.3835	0.05%	0.3940	0.15%	0.4132
MOLC DS content	1,5%	0.3835	0.05%	0.3940	0.15%	0.4132

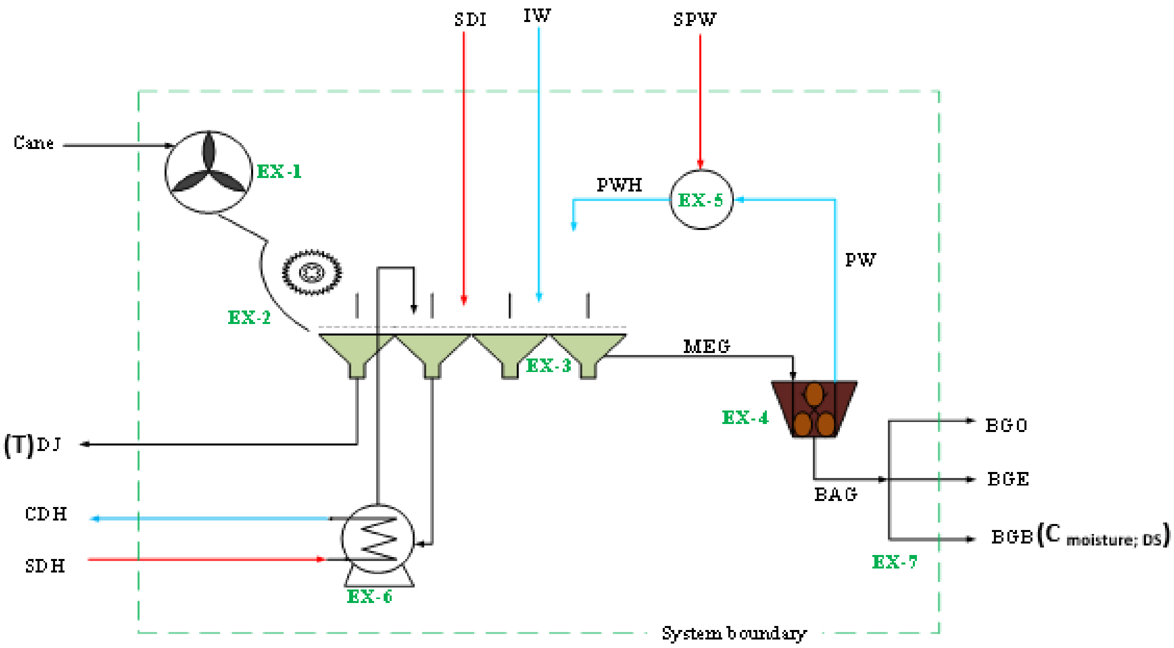
Table S-8-7: The parameters and methods used for sensor selection using genetic algorithms

Parameter type	**Parameter value**
Number of genes per chromosomes	41
Population size	500
Maximum iterations	100
Chromosome selection method	Roulette wheel selection
Crossover method	Single-point crossover
Probability of crossover	0.8
Mutation rate	0.2

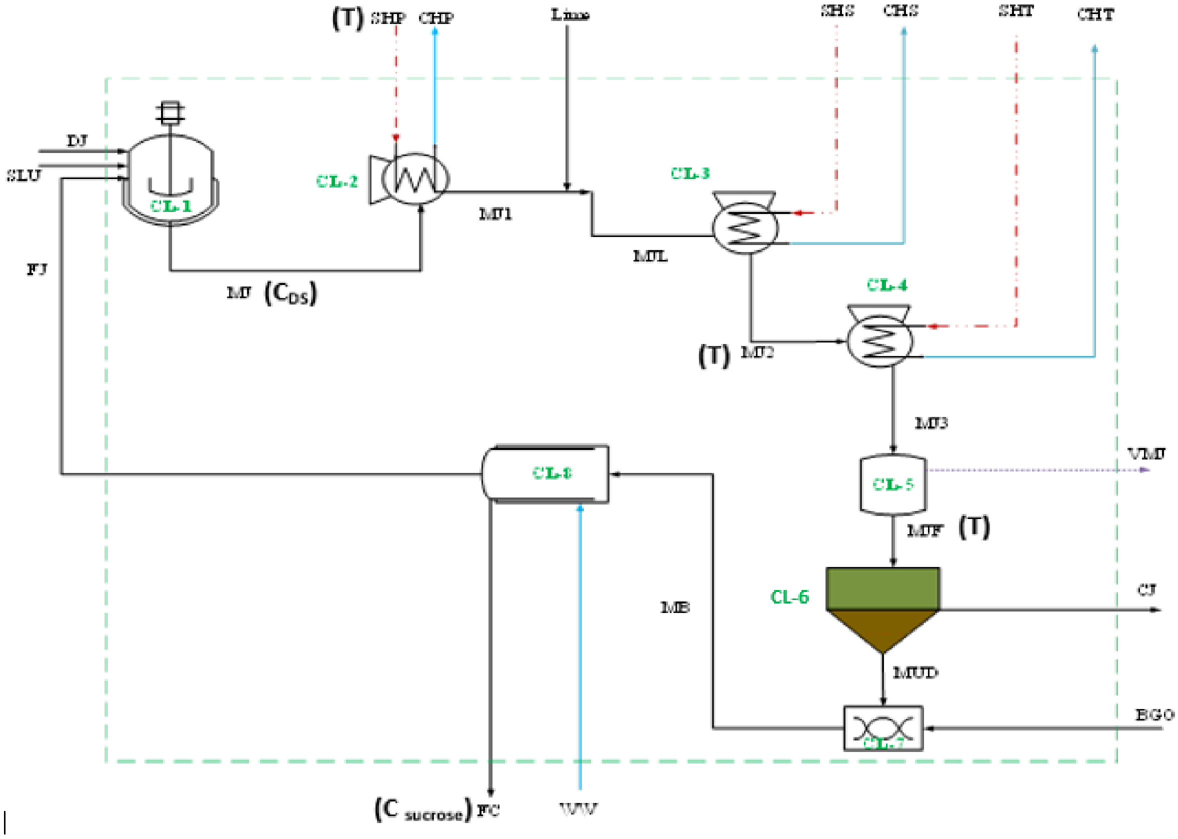
Appendix D: Optimal sensor placement diagrams

The diagrams below illustrate the optimal sensor placements allocated for the sugarcane mill extraction, clarification, evaporation, crystallization, sugar drying, and utility sections. The symbols T, P, and C_i are used to illustrate the temperature, pressure, and concentration measurements. The subscript "i" in C denotes moisture, DS, or sucrose content of the respective stream.

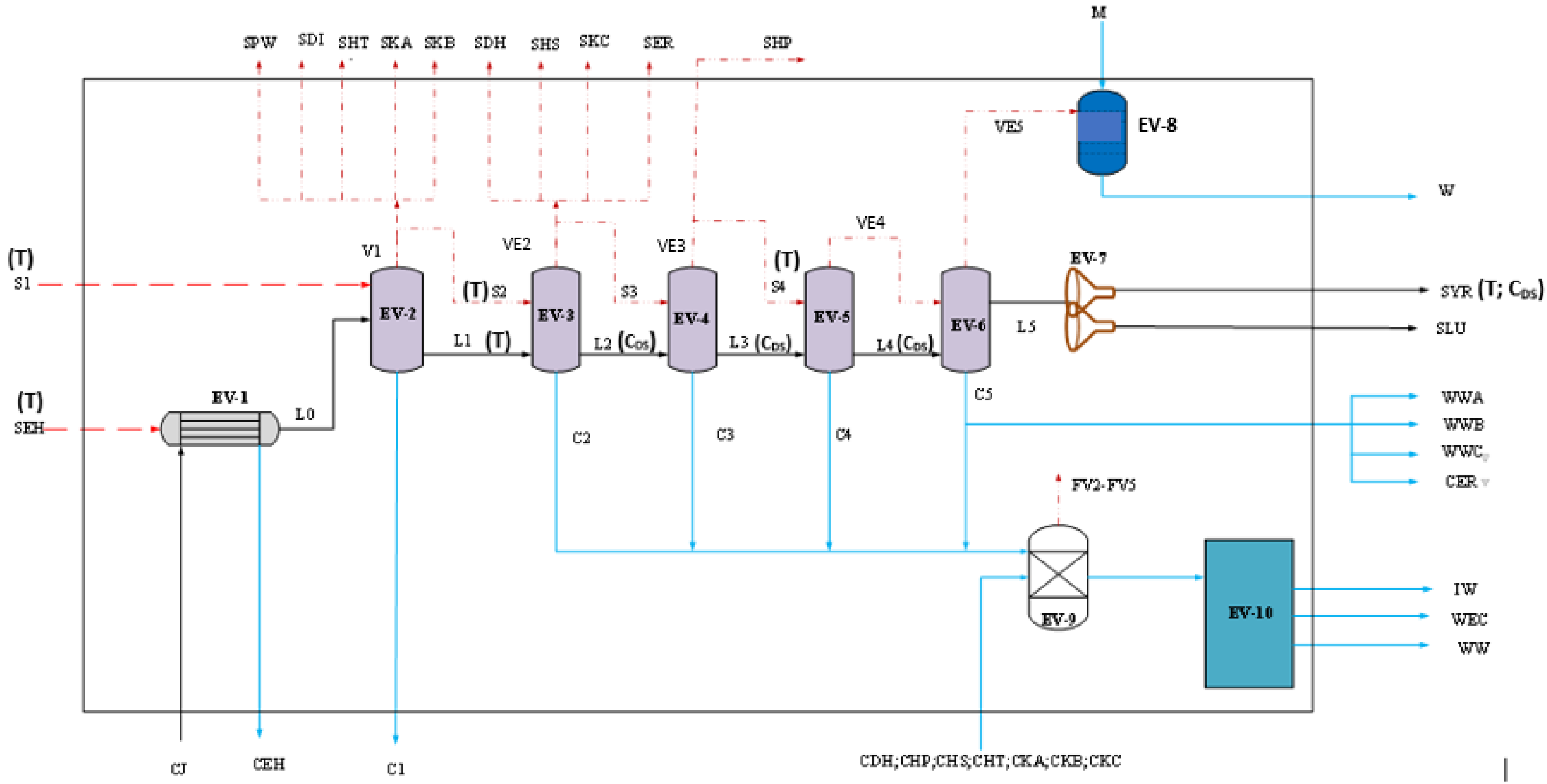
Extraction unit



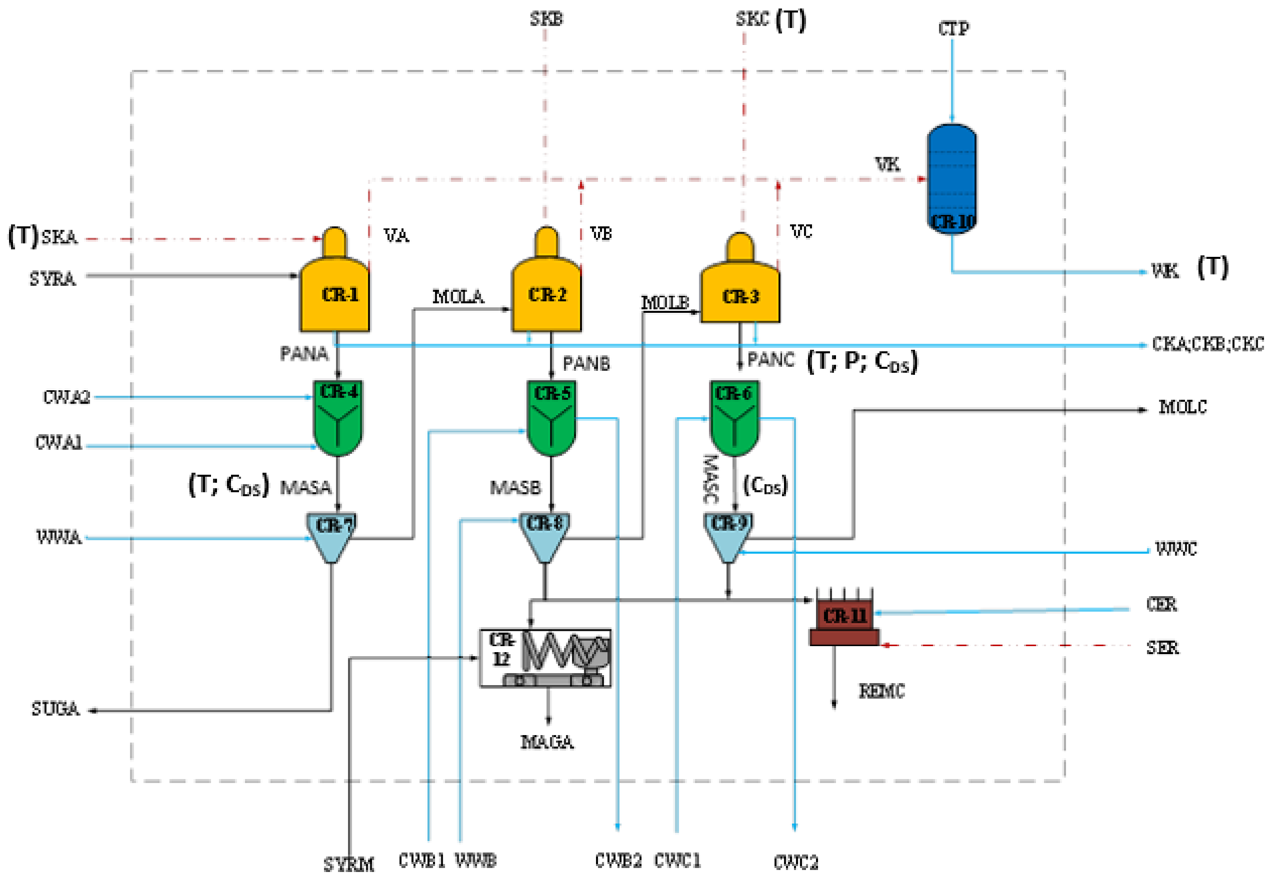
Clarification unit



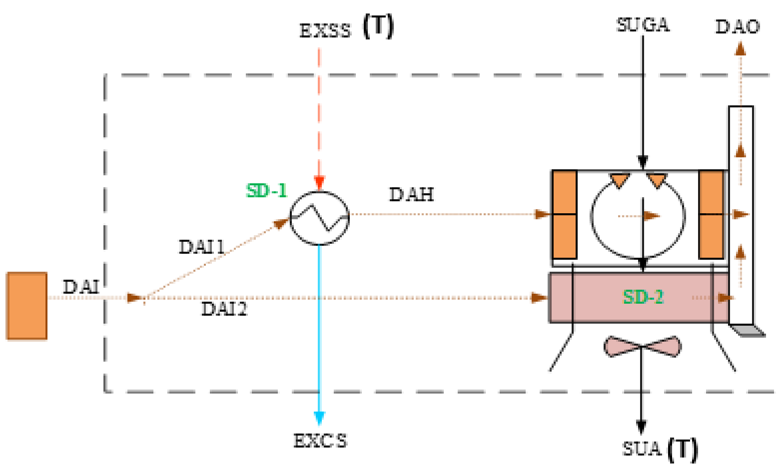
Evaporation unit



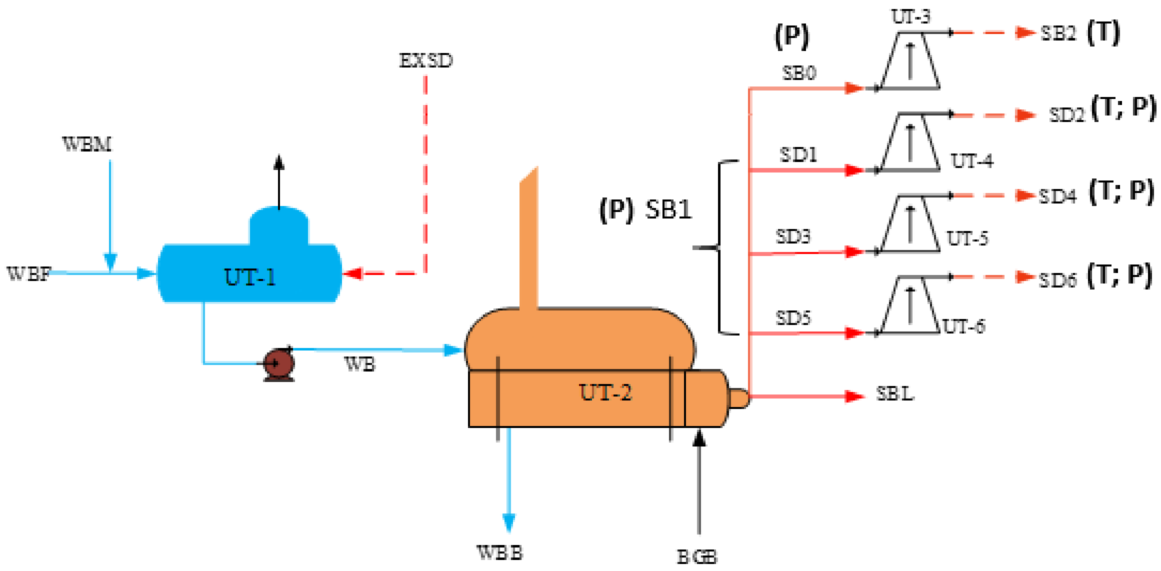
Crystallization



Sugar drier



Boiler and turbogenerators



Cooling tower